FINAL REPORT

Realizing the Potential of the Effective Area Model: Refining the Software and Incorporating Recent Advances to Maximize Usefulness on Military Installations

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14. ABSTRACT

Landscape structure is increasingly recognized as a factor that can greatly impact habitat quality. Despite this, the tools to understand how landscape context impacts habitat quality, largely felt through edge effects, have been slow to develop. Yet research suggests that observed edge responses are increasingly predictable and offer an avenue to understand landscape-scale responses to management actions for both individual species and communities of organisms. We developed a series of tools to harness either field data or basic natural history information about local ecological communities in order to predict responses to changes in landscape structure. The cornerstone of this toolkit is the Effective Area Model (EAM). The EAM takes information about local edge effects and extrapolates them over landscapes, offering the user predictions of species responses or useful metrics on landscape structure. In addition to this tool, we developed R-packages to characterize edge responses from field data and also to help users process and visualize output from the EAM. We have implemented this approach to management by demonstrating its use on two bases: Ft. Benning, GA and Ft. Hood, TX. Our results show how managers can use information from the EAM to help plan management actions or shape thinking regarding large-scale dynamics. We further show how simple metrics may sometimes suffice to understand responses to landscape changes, but also when more nuanced metrics may be necessary to help managers grapple with complex responses across a community of organisms. Finally, we present an approach to incorporating output from the EAM (or other models) into installation maps, offering a straight-forward approach to landscape-scale management.

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List of Acronyms

ACUB	**Army Compatible Use Buffer**
AIC	**Akaike's Information Criterion**
BRAC	**Base Realignment and Closure**
CBF	**Cross-boundary forager**
DNE	**Distance to Nearest Edge**
DOD	**Department of Defense**
Dmax	**Distance of maximum edge influence**
Dmin	**Distance edge density extends into habitat**
EAM	**Effective Area Model**
ESRI	**Environmental Sciences Research Institute**
GIS	**Geographic Information Systems**
SEMP	**SERDP Ecosystem Management Project**

Bird Species Codes:

BAWW	**Black-and-white warbler**
BCVI	**Black-capped vireo**
BCTI	**Black-crested titmouse**
BEWR	**Bewick's wren**
BGGN	**Blue-gray gnatcatcher**
CACH	**Carolina chickadee**
CARW	**Carolina wren**
GCWA	**Golden-cheeked warbler**
MODO	**Mourning dove**
NOCA	**Northern cardinal**
NOMO	**Northern mockingbird**
PABU	**Painted bunting**
RCW	**Red-cockaded woodpecker**
SPTO	**Spotted towhee**
WEVI	**White-eyed vireo**
YBCH	**Yellow-breasted chat**

Ft. Hood "Pseudo-species"

PNIN	**Mature pine specialist**
PNED	**Pine generalist**
HWIN	**Hardwood interior**
HWED	**Hardwood edge**
FORG	**Forest generalist**
SHRB	**Shrub (in forest) specialist**
ESDP	**Forest edge specialist**

Ft. Hood edge variants

T100	**Typical (same as HWIN)**
T200	**Typical with Dmax 200**
A100	**Skewed with Dmax 100**
A200	**Skewed with Dmax 200**
XT25	**Dmin at 25m**
XT50	**Dmin at 50m**

Keywords

Fragmentation, landscape, edge effects, birds, decision support system, scenario modeling, habitat modeling

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Programming of the Effective Area Model (EAM) was completed by Jared Andre at Iron Rim, LLC based on some initial work by Timothy Bricker. Andra Doherty completed all Ft. Hood mapping of cover classes and point edge segment maps. Andra also developed StopNGo scenario maps and ran many of our EAM runs. Finally, Andra designed our Edge Effect Resource Center website. Other technicians who helped develop scenario maps include Paul Robey, Brian Scherer and Michael Fisher. Michael also helped run scenarios. Tony Vernon developed the EAM manual into an online version and also helped run scenarios. This project is a continuation of work done in collaboration with Arriana Brand, James Battin, and Barry Noon who contributed to our development of the various models. The original version of the EAM was developed for ArcView 3.2 by Haydee Hampton.

1. Abstract

Landscape structure is increasingly recognized as a factor that can greatly impact habitat quality. Despite this, the tools to understand how landscape context impacts habitat quality, largely felt through edge effects, have been slow to develop. Yet research suggests that observed edge responses are increasingly predictable and offer an avenue to understand landscape-scale responses to management actions for both individual species and communities of organisms. We developed a series of tools to harness either field data or basic natural history information about local ecological communities in order to predict responses to changes in landscape structure. The cornerstone of this toolkit is the Effective Area Model (EAM). The EAM takes information about local edge effects and extrapolates them over landscapes, offering the user predictions of species' responses or useful metrics on landscape structure. In addition to this tool, we developed R-packages to characterize edge responses from field data and also to help users process and visualize output from the EAM. We have implemented this approach to management by demonstrating its use on two bases: Ft. Benning, GA and Ft. Hood, TX. Our results show how managers can use information from the EAM to help plan management actions or shape thinking regarding large-scale dynamics. We further show how simple metrics may sometimes suffice to understand responses to landscape changes, but also when more nuanced metrics may be necessary to help managers grapple with complex responses across a community of organisms. Finally, we present an approach to incorporating output from the EAM (or other models) into installation maps, offering a straight-forward approach to landscape-scale management.

2. Objectives

We had two complementary sets of objectives for this project. The first set of objectives was to make several improvements and additions to our Effective Area Model (EAM) toolkit. The EAM is a habitat model where landscape context, in the form of explicit consideration of habitat edges, is incorporated into predictions of habitat quality. However, the development of this software program to implement the EAM within a Geographic Information Systems (GIS) platform only facilitates one step in our overall approach to landscape-scale management. The EAM toolbox also contains an assortment of programs, scripts and guiding documents to help researchers implement a program of large-scale, long-term management for multiple species. Specifically, we have:

1. developed a workflow to guide researchers and natural resource managers through our modeling program;
2. continued to refine our models to aid in parameterizing the EAM;
3. improved the EAM and re-written it for the current generation of ESRI GIS software products; and
4. developed custom R-scripts for key analytical steps in the process.

The second set of objectives focuses on our continued work with managers at Forts Hood and Benning to apply our landscape modeling approach to their management challenges. Through the targeted application of the EAM and associated tools at both of these bases, we not only tested and improved our process and products (see first objective), but expanded our basic understanding of landscape-scale processes and the ecological impacts of fragmentation. Specifically, at each base we have:

1. developed scenario maps related to habitat restoration and to the use of roads and trails;
2. developed edge response functions for target species at each base;
3. implemented the EAM for each target species on each scenario map; and
4. analyzed the EAM output and determined how the results could be used to help guide management.

3. Background

3.1 Introduction

The military, along with other major land owners, is faced with increasing pressure to manage their resources to meet multiple objectives, including military readiness, protecting endangered species, and, increasingly, to protect biodiversity and wildlife habitat in general. It is often difficult to balance all of these competing goals, and a lack of appropriate tools can make decision-making difficult. This project seeks to aid managers in implementing large-scale, long-term management plans to help maintain the health of ecological communities. These tools can be used specifically for endangered species management or to balance the needs of endangered species with those of the larger ecological community. The cornerstone of our project is the Effective Area Model (EAM, Fig. 1). This model allows the influence of patch context (measured via edge effects) to be considered in weighting habitat quality throughout a landscape.

One of the critical factors underlying the impacts of habitat fragmentation is the increase in the amount of habitat edge as patches become smaller (Sisk et al. 1997) and is one of the critical components to consider when managing landscapes (Lindenmayer et al. 2008). Edges influence habitat quality because adjacent habitat influences the flow of biotic and abiotic material and gives access to neighboring resources (Ries et al. 2004). Further, edges are critical to understanding other components of fragmentation. Indeed, most area effects are likely scaled-up edge effects (Fletcher et al. 2007) and that edges are an important component to understanding connectivity (Haddad and Baum 1999).

While hundreds of published accounts have specifically documented the varied responses of organisms to the presence of habitat edges (Ries et al. 2004), until recently the only approach to consider edge effects over a landscape was to employ core area models (Temple 1986, Laurence and Yensen 1991) which effectively constrain management consideration to patch interiors and ignore edge zones, which often constitute the vast majority of heavily-utilized landscapes. These models are of limited utility because they only apply to extreme habitat specialists that avoid all habitat edges. In reality, most species show a variety of edge responses, including many that show higher abundances near some edges (Ries et al. 2004). In order to consider the full range of responses that multiple species may show to the great variety of edges that exists in real landscapes, managers need a tool flexible enough to consider the specific responses of each species of management interest to each unique edge type that exists on the landscape.

The EAM (Sisk et al. 1997) builds on the foundational core-area concept, but offers a comprehensive approach, based on the assumption that the quality of habitat within each patch may be influenced by the response that each species shows to adjacent habitat (Fig. 1a). Through previous funding received from the Strategic Environmental Research and Development Program (SERDP), the concept of the EAM was developed into a useable tool via a programming extension integrated into ArcView 3.2 (Sisk et al. 2003, Fig. 1b). In addition, we developed a tool to predict basic edge responses when data are lacking (Fig. 1c). Combined, these tools allow managers and researchers to predict, over an entire landscape, the changes in habitat quality due to landscape structure (including patch size, shape and each type of surrounding habitat) for any species of interest. Recent work shows that our edge response model is successful at predicting observed edge responses in the majority of cases (Ries et al.

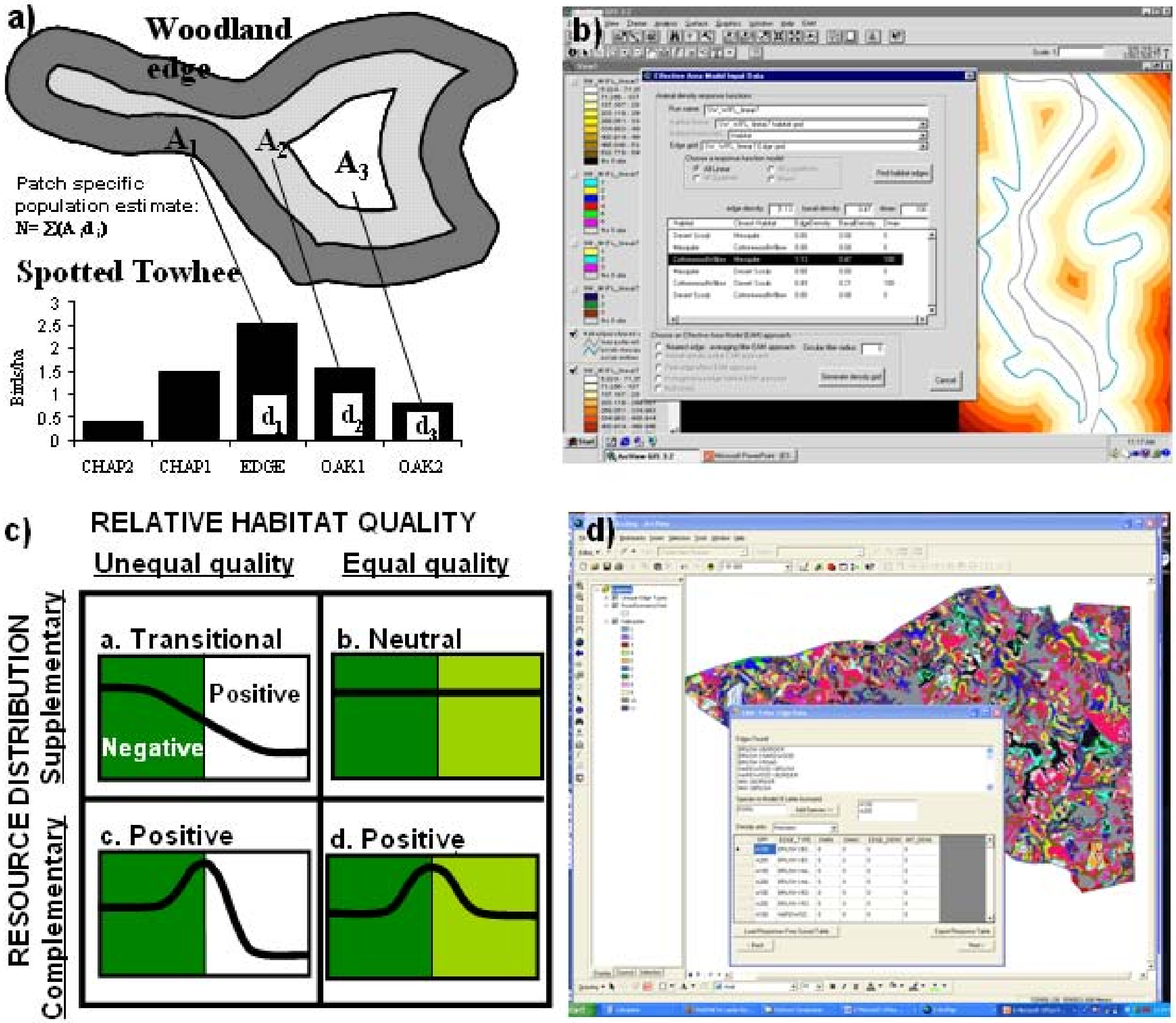


Figure 1. The Effective Area Model (EAM) Toolkit. The concept of context-dependent edge responses (a) was originally implemented in ArcView 3.2 under SERDP funding (b). In addition, a simple model was developed for managers to predict edge effects even in the absence of field data (c). The EAM has now been developed for the current generation of ArcGIS products (d) and has several improvements.

2004, Ries and Sisk 2008) and that the EAM does better at predicting community responses compared to models that ignore edges (Sisk et al. 1997, Ries 2003, Brand et al. 2006).

This SERDP-funded project focused on further developing our toolkit by continuing to work with managers at two military bases, Ft. Hood in Texas and Ft. Benning in Georgia. At both of these bases, we worked with managers to develop scenarios that reflect future decision-making and gather ecological data to develop the most realistic edge functions. Past work had shown that incorporating information on how edges modify habitat quality could influence management priorities and conservation outcomes (Ries and Sisk 2005). Under SI-1597, we have updated the EAM to the current generation of geographic information systems (GIS) produced by the Environmental Sciences Research Institute (ESRI), and added features to facilitate its use (Appendix A). We also have expanded the EAM toolkit by developing automated workflows of some critical steps to help managers and researchers more easily implement our modeling approach. And through our continuing work with Ft. Hood and Ft. Benning, we are developing a framework for how land use and natural resource management may impact multiple species over long time frames.

3.2 Integrating the EAM Toolkit into an Overall Workflow

We have developed an approach to landscape-scale habitat management that is applicable for both scientists and managers. To make tractable the implementation of this approach (or even just portions of it), we developed a formal workflow that incorporates a series of tools that are part of an EAM toolkit. To disseminate the tools and approach, we launched a website called the "Edge Effects Resource Center" that describes each step in this process and the tools available to facilitate the implementation of each step. The website is now live and can be viewed at: http://www.clfs.umd.edu/lries/EERC/EERC.html. All tools are available to be downloaded from this site, along with instructions and guidelines. Tools will also be made available through on-line appendices linked to future peer-reviewed publications that result from this work, and we will specifically target journals for publication that provide on-line appendices. Finally, we plan to distribute our R-package that we developed through the R community mechanisms that allow packages to be downloaded by anyone that has access to R, an open-source statistical software package that has become popular in the scientific community.

The first steps in our process involve identifying management needs and developing scenario maps that reflect the range of possible management choices. The challenges presented to managers vary from site to site, but there are many common themes. Because the challenges of each site are unique to the local species, threats and decisions being made, we did not attempt to develop a tool that would automatically generate scenario maps for all sites or types of question. Instead, we developed guides to scenario development that will pertain to many management challenges. The next key step in implementing our management approach is developing edge response functions that are used in the EAM. One of the major challenges that we dealt with is the limited amount of field data that are available for model parameterization. We therefore developed different approaches to edge response parameterization, depending on whether or not field data are available. Many bases will have no species-level field data, and our main tool to develop responses in these cases is a conceptual model to predict edge responses that can be used for any species at any edge type (Ries and Sisk 2004). The minimum information necessary to make predictions includes descriptions of habitat associations as well as knowledge of any complementary resources that are present in adjacent habitats. We also developed models and tools for edge response parameterization when field data are available. The core EAM model uses a GIS interface to allow users to predict distributions of target species across each of the different scenario maps created to reflect alternate management choices. We developed this overall workflow structure based on our experience working on two demonstration sites: Forts Benning and Hood.

3.3 Demonstration Sites

Ft. Benning

Ft. Benning is an active 75,000 ha installation located in southwestern Georgia. As part of SERDP's Ecosystem Monitoring Program (SEMP), there has been an ongoing effort to understand the impacts of military activities on the natural ecosystem. Ft. Benning lies in the Fall Line transition zone between the Southern Appalachian Piedmont and Coastal Plain (Olsen et al. 2007). The base supports highly diverse pine and hardwood communities that were once dominated by pine, but have since been degraded by timber extraction and fire suppression (Olsen et al. 2007). Currently, there is a complex of forest stands that shows a wide diversity of dominant species and age classes. Based on spatial data received from Ft. Benning, the vast majority of the base is forested (Fig. 2a). One of the main goals of the Ft. Benning managers is to return this landscape to pre-European conditions, especially to benefit its main listed species, the red-cockaded woodpecker (RCW). However, Ft. Benning is currently undergoing a major landscape-scale transformation under the Base Realignment and Closure (BRAC) program, where up to ~14,000 ha are planned for transformation to accommodate increased troop levels at the facility (Fig. 2b). Although we have not been able to find out exactly how each of those areas is going to be modified, they are expected to comprise largely open habitat, although at least some of the areas will remain partly forested (Don Imm, *personal communication*). We received this map late in our project and so have only been able to include it peripherally in our modeling efforts.

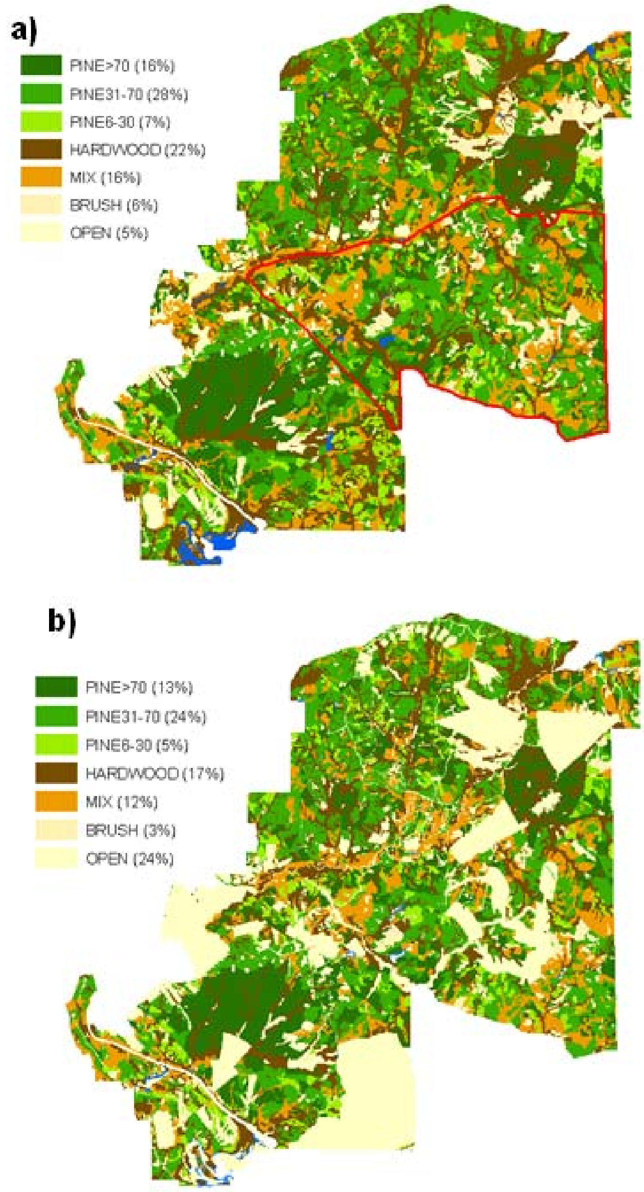


Figure 2. Ft. Benning's current habitat configuration (a) and configuration after planned modifications due to BRAC changes (b) assuming transformations to open habitat. Road modeling was focused in only a portion of the base (red outline)

Based on our previous modeling and demonstration work, we found that modifying the landscape could have highly variable effects on target species, and that threshold effects may be apparent (Ries and Sisk, 2005). We have followed up on that work by expanding our road modeling scenarios, especially by adding multiple replicates of each road density category – and by using the patch statistics now generated by the EAM to determine how different landscape factors underlie the variability seen in EAM predictions.

We have also undertaken two new scenario modeling efforts. The first addresses how choosing sites for restoration may impact the larger ecological community. We did this by developing a set of scenarios where we simulated both restoring stands to pine and allowing the forest to age naturally. This process culminated with a set of maps that likely resembles a forest structure that is more similar to one found prior to European settlement. The predicted impacts of this time-series of maps are compared to the current planned BRAC actions. The second modeling effort is based on collaboration with a SERDP-funded group at the University of Washington led by Josh Lawler (SI-1541). Their group has worked to develop a series of scenarios that show the potential for continuing BRAC activities over a 90-year time span. The Lawler group shared these maps with us allowing a collaborative effort to compare the results of our two modeling approaches. Unfortunately, these maps were developed before the final plans for the current BRAC activities were made available, and the habitat loss modeled over the 90-year timeframe (~3000 ha) does not approach the amount of forest conversion planned for the current BRAC project (~14,000 ha). Further, the Lawler group is now conducting this modeling with an aging forest, so a direct comparison of results may not be meaningful. Because the scale of this modeling effort is different from the current planned BRAC activities, we have framed these results as a comparison of what happens when habitat is removed locally in large pieces rather than when patch-level conversion is minor, as is the case with adding roads and trails.

Ft. Hood

Our other demonstration site, Ft. Hood, is an 88,500 ha active military installation located on the Edwards Plateau in central Texas. The habitat consists mainly of a mixture of grassland meadows and oak-juniper woodlands in varying successional stages (Fig. 3). The natural interspersion of these habitat types creates distinct habitat edges (Fig. 3b) that may exert a significant influence on local populations. Ft. Hood has two endangered species that receive the majority of management attention, the golden-cheeked warbler (GCWA) and black-capped vireo (BCVI). Ft. Hood established a network of 698 bird survey points that can be used for generating parameter estimates for the EAM (Fig.

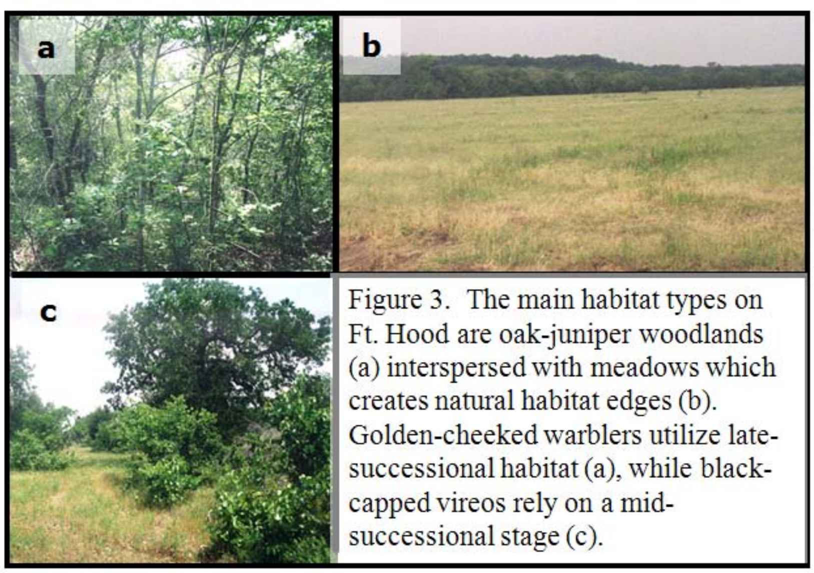


Figure 3. The main habitat types on Ft. Hood are oak-juniper woodlands (a) interspersed with meadows which creates natural habitat edges (b). Golden-cheeked warblers utilize late-successional habitat (a), while black-capped vireos rely on a mid-successional stage (c).

4a). For this project, we are expanding our work on road networks at Ft. Benning and applying those principles to Ft. Hood. We also initiated a new type of management approach, where we explored how the competing needs of the two focal species on the base might be balanced.

Unlike Ft. Benning, Ft. Hood has neither a road network map nor a full coverage classified habitat with cover classes relevant to BCVI and GCWA. Ft. Hood does maintain a full coverage vegetation alliance map that shows dominant plant communities throughout the base (Charlotte Reemts, *personal communication*). However, because GCWA and BCVI respond most strongly to successional stage as well as plant alliance, those maps can not be used to infer habitat quality for GCWA or BCVI. This is true for many other local species as well. Instead, Ft. Hood maintains two separate maps that show the extent of GCWA and BCVI habitat. Our challenge in applying the EAM on this base was that we needed to develop a map that showed not just the extent of focal habitat, but also identified all surrounding habitat types (because the EAM makes its predictions based on focal habitat *and* patch context). Because successional stage is critically important, we used satellite imagery to visually classify all habitats surrounding each of the patches containing the 698 survey points – as well as the total area within a focal modeling area (red outline in Fig. 4a). We also developed a road network map, again using satellite imagery (Fig. 4b).

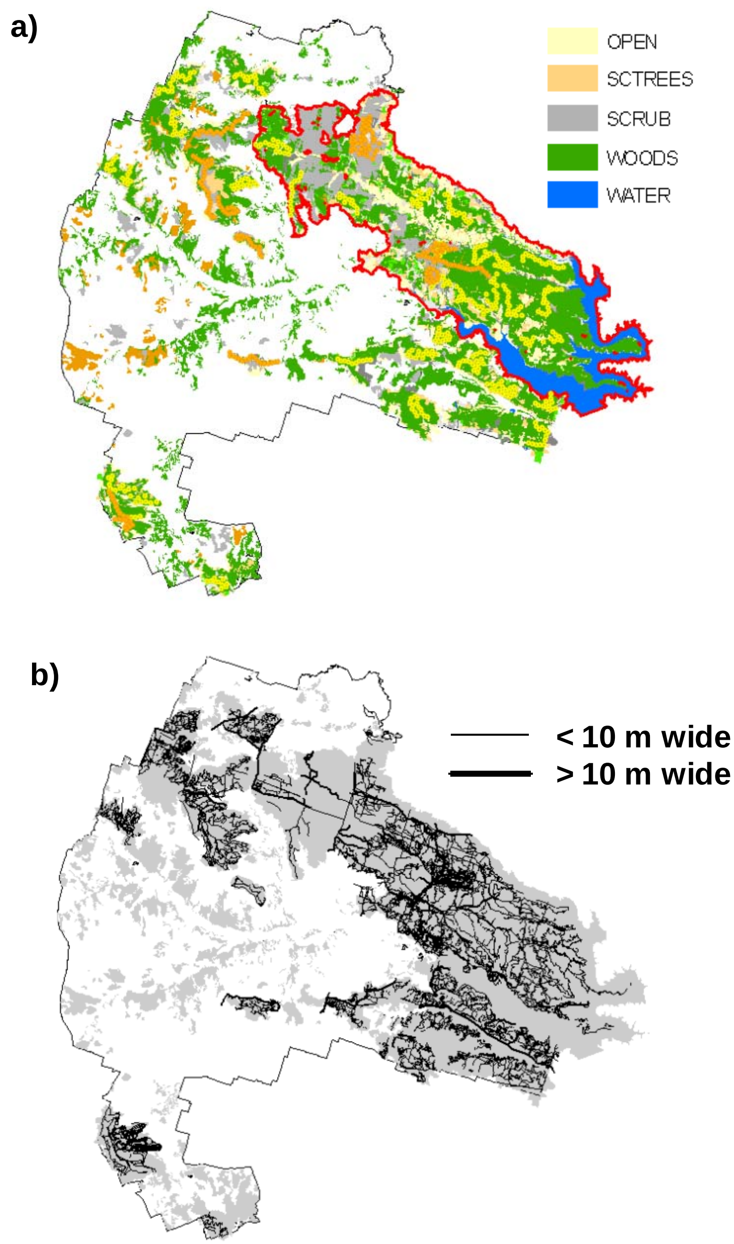


Figure 4. Habitat cover (a) and road network maps (b) for Ft. Hood. An extensive network of GCWA (yellow with dot) and BCVI (orange) point counts are shown in (a) along with our focal area for modeling (outlined in red).

These two time-consuming tasks were first carried out in 2008. By necessity, we focused on 10 cover classifications that were ultimately combined into 4: WOODS (GCWA habitat), SCRUB (BCVI habitat), SCTREES (areas with "scattered trees" that contained habitat that is less suitable for BCVI and very marginal for GCWA), and OPEN (habitat that was unsuitable for both species). In the process of developing the maps, we noticed that many areas that appeared structurally to be GCWA habitat were not classified as such. In an October, 2008 visit to Ft. Hood, we presented these classifications to the staff in the natural resources department and they agreed that these were reasonable. They also confirmed that some GCWA (WOODS) habitat had not been identified on their earlier maps and provided us with a new map that had been updated in September of 2008. Since our analyses of Ft. Hood's bird data depended on the best maps, we were forced to recreate our habitat map using the newest GCWA habitat cover, and this took another several months, delaying our scenario modeling efforts at Ft. Hood. Our efforts to develop these maps were focused in all areas that contained bird survey points, and also a portion of the base that would be the focus of our modeling efforts. We finalized both our habitat map (Fig. 4a, the modeling area is outlined in red) and the road and trails map (Fig. 4b) in June 2009. We used these maps to classify each of the 698 survey points according to their habitat type and edge type, and then we selected points to develop edge response functions for the EAM. The resulting edge response functions were used to carry out two modeling exercises on Ft. Hood: examining the role of road networks and balancing the needs of competing species.

4. Materials and Methods

Our project relies on the vast stores of spatial and ecological data that are available to varying degrees on military bases, in this case at Forts Benning and Hood. Therefore, no field work was performed. At each base, we used the available data to implement each step in our modeling process. At the same time, we developed automated tools, including the EAM and R packages, and conceptual tools, such as our edge effects model, for scientists and managers to use in applying our modeling framework. In this section, we describe the overall workflow that we used to apply our modeling framework over the three-year project period at both bases. Our formal workflow includes six steps: 1) identify management needs, 2) develop scenario maps, 3) develop edge response functions, 4) run scenarios through the EAM, 5) process, visualize and analyze EAM output, and 6) develop management recommendations. We have focused our efforts on automation and tool development on steps 2-5.

4.1 Step 1: Identify Management Needs

Our first challenge was to identify questions facing managers that have landscape-scale implications. We met several times with natural resource managers at both Ft. Benning and Ft. Hood and, after several pilot projects, focused on two general questions: how does road density impact ecological responses, and how could patches best be chosen for restoration efforts. In general, we assume that these choices are driven largely by logistics and constrained by the specific needs of the focal, listed species on each base. Through our modeling efforts we attempted to balance these needs while incorporating consideration of the larger ecological community. At both demonstration sites, we found it challenging to establish strong linkages with our research to actual management decisions. However, we do believe that our efforts and the generally supportive nature of management staffs at both installations were sufficient to guide research in practical directions and prepare for future applications.

4.2 Step 2: Develop Edge Response Functions for Target Species

In order to extrapolate species' edge responses and predict overall population changes based on the alternate landscapes illustrated in our scenario maps, we developed edge response functions for each species of interest. Edge responses are described via four parameters (Fig. 5a), three of which were programmed in the original EAM: density in the interior habitat, density at the edge, and the distance into the patch of any edge influence (Dmax). We also included in the new version of the EAM a parameter that allows the density at the edge to extend into the habitat (Dmin). The combination of these four parameters can be used to capture the variety of different edge response patterns that have been reported in a vast ecological literature (Fig. 5b). Because the availability of empirical data is highly variable, we were required to take two different approaches to estimating edge response functions. When data were available (as they were at Ft. Hood), we used analytical techniques to develop edge response functions. When no data were available (as for Ft. Benning), we used our edge response model (Fig. 1c) as well as any relevant information from the literature.

One of the fundamental challenges of studying and using edge responses in conservation and management has been the best way to characterize edge response functions analytically. This has been the subject of great attention in the literature and, recently, some researchers (including ourselves) had settled on piecewise regression as the best approach (Toms and Lesperance 2003, Brand et al. 2006). Yet during this project, we made substantial advancements in this area by developing a new tool to implement a model published in 1994 by J. Malcolm. This mathematical model is useful in that it can incorporate information about complex edge geometry and it returns parameters, either directly or indirectly, that are used in the EAM. Although a well-known model, it has never been implemented due to the intractability of the mathematics necessary for its implementation in complex landscapes. To address this challenge, we developed an R-package ("edgefx") that implements the model in any landscape (Appendix C). This new method is described in section 5.2. We implemented this approach at Ft. Hood where we had field data for parameterization.

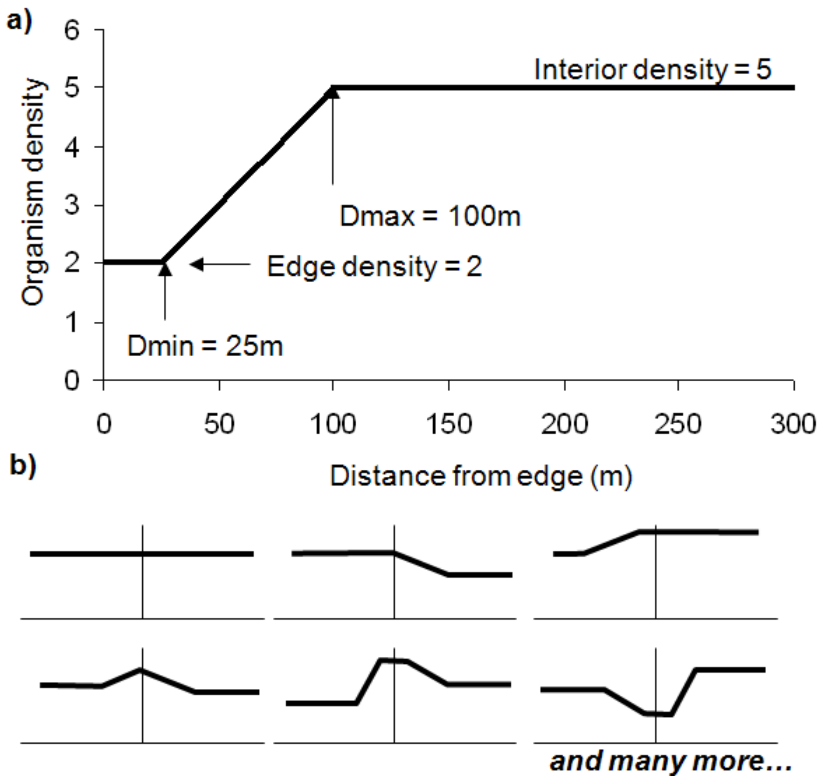


Figure 5. The four parameters (Dmin, Edge density, Dmax, Interior density) required for the EAM (a) combine to capture a range of patterns across an entire edge gradient (b).

The best-studied species at Ft. Benning is the red-cockaded woodpecker (RCW), a federally-listed species that receives the majority of management attention. Our initial data explorations revealed no relationship with edges and, indeed, this species is known to be tolerant of edges and even prefer them (Ross et al. 1997). Further, detailed models for RCW management were already developed by Jeff Walters of Virginia Tech (SI-1469). Therefore, we focused on the remainder of the bird community, but, when appropriate, considered how management of the RCW might impact other species. Since there are no field surveys that are able to provide data for the statistical determination of edge response functions for any other species at Ft. Benning, we used our edge response model (Fig. 1c) to generate response functions for a suite of "characteristic pseudo-species" that represent groups of species with similar habitat associations. We took this approach because we lack all but the most basic information on the distributions of bird species on Ft. Benning. Further, every test of our edge response model has shown that only a portion of the community seems to be sensitive to edges (Ries et al. 2004). Therefore, we have undertaken a new research focus, which is to develop tools to identify the most sensitive species and target them for modeling (Ries and Sisk, *in press*). In the meantime, since we had no way of determining which members of the Ft. Benning community might be most sensitive to edges, we grouped the species into "response clusters" (groups of species that would be expected to respond similarly to edges, assuming they are edge-sensitive). We then developed parameters for one characteristic "pseudo-species" to represent each group. Parameter development for each pseudo-species was inspired by one of the members of each "response cluster". The predicted responses of each pseudo-species are likely to reflect the responses of sensitive species in that group.

4.3 Step 3: Develop Scenario Maps

The next step in our process is to develop scenario maps that reflect a range of possible landscape configurations that might result under different management choices. For our demonstration sites, we focused on patch restoration and road networks. This required developing specific scenarios and targeting specific areas of the base. As noted in step 1, we found this to be the most challenging aspect of our project because obvious landscape-scale decisions were not a focus of management at that time. We have been working continually with resource managers from Ft. Hood and Ft. Benning to refine our approaches to reflect more closely the types of decisions that are actually faced by natural resource managers and training coordinators. For road scenarios, we focused on a portion of the base and iteratively added or deleted roads from the existing road network to simulate increasing or decreasing activity levels. For restoration scenarios, we developed maps where we iteratively or individually "converted" patches from one habitat to another within our GIS maps.

In developing our multiple scenarios, we found it useful to divide scenarios into two types: The first type are ACTION scenarios, where the structure of the landscape is altered in some discrete manner, i.e., by adding (or removing) a road or firing range. On the other hand, CONVERSION scenarios are one where an already defined patch on the landscape is simply converted into another type, for instance through planned restoration or burning. For ACTION scenarios, it was necessary to intersect and perform several queries on each scenario map to process it for use in the EAM. To facilitate this process, we used a helpful tool available in the ArcGIS environment called "model builder". We used our examples as a basis for a brief overview that could be adapted by managers to facilitate their own scenario processing (available at the EERC website).

For all our scenario sets (except one) we developed replicate maps of each scenario. This allowed us to explore the impacts of how different configurations of the same management decision (i.e., level of action) might impact our conclusions. This replication of modeled landscape scenarios is vital for testing the overall approach and a requisite for publishing results in peer-reviewed journals. However, it seems unlikely that managers would generally attempt to develop replicate maps for the same management option, so we attempt to also interpret our results based on what information might come from a single scenario map. Further, in working with managers over the past several years, we found that one of the challenges is that scenario modeling is not an approach that is generally employed by managers, so its full adoption may not occur in the short-term. As a more tractable alternative, we have begun developing a new approach that we call "StopNGo" mapping. This approach allows managers to develop a series of rules to facilitate the choice of either ACTION or CONVERSION sites. Those rules are then coded visually into a single ArcGIS map that allows managers to see where on the landscape they can best meet their objectives, without restricting them to any particular choice. We present this new approach in section 5.4.

4.4 Step 4: Run Scenarios through the EAM

After developing maps that reflect different management scenarios and edge response functions that reflect how different species respond to the landscape, we combined these two classes of data within the EAM platform (Appendix B). The EAM takes each edge response function, extrapolates the functions over the entire landscape and returns a spatial data grid showing the predicted density of each modeled species in each pixel. One density grid is returned for each species. Based on those density grids, the EAM summarizes predicted densities and total population sizes at the landscape, habitat, or patch scale. The EAM also returns a table of statistics for each map, including the unique edge types and the mean distance to edge for each unique edge type. The statistics output in these two tables can be summarized by any field in the attribute table of the original polygon map (generally, a unique identifier for each patch, but it could be any field chosen by the user so hereafter we refer to them as “units”). These statistics form the basis of the analyses that are done to evaluate each scenario and also identify mechanisms that drive any observed patterns in the data. The EAM has an integrated user guide to facilitate its use.

4.5 Step 5: Process, Visualize, and Analyze EAM Output

The EAM produces a large amount of output, and in a format that can be easily used to graph some basic results. However, we have found that in order to visualize more complex results and do analysis, it is necessary to take several steps to process EAM output. First, if multiple scenarios were run, then output tables must be concatenated (each run produces separate output). If performing analyses that rely on classifying edges as to their specific impact on each species, a separate table must be created that indicates for each species at each edge type whether responses are positive, negative or neutral. To do this, we create a table called “patch summary” that indicates how much edge of each type are contained in each unit as well as the mean distance to edge and other statistics such as total distance to edge, % habitat change and the total number of edge types within that unit. Finally, we create a table called “species summary” that indicates the predicted density and total population size for each unit for both the EAM and NULL models, and also the proportion of edge in each unit that has a positive, negative and neutral effect. The creation of these last two tables (“species summary” and “patch summary”) requires multiple manipulations and takes several hours to implement manually. To make this process easier, we developed an R-package called “REAM” that creates these two essential tables (Appendix D). To run the package, the user must provide four types of tables: 1) a table of edge response parameters (the same Edge Response Parameter table that is used in the EAM), 2) a Scenario Table that indicates for each scenario what was the major action taken (i.e., amount of habitat removed or added or restored for each scenario), 3) the series of “species statistics” tables output by the EAM, and 4) the series of “edge statistics” tables output by the EAM.

The “species summary” and “patch summary” tables can be used to create any number of graphs to visualize the data and could support a wide variety of analytical approaches. Because each researcher or manager might have different motivations for performing their analysis, it is hard to anticipate exactly which graphs or analyses will be most useful. Despite this, we have included a function in the REAM package that outputs for each species modeled two basic graphs that we expect to be of broad interest to managers or scientists. One shows the total population predicted from the NULL and EAM models for each scenario (Fig. 6a); the second shows density predictions from the EAM by unit (usually patch) for each species in each habitat type (Fig. 6b). If additional graphs are necessary, the user can easily generate any graphs they wish from the tables using any number of packages (i.e., Excel, R, SAS, etc.). Finally, we developed an approach to analyzing output data that ranges from simple metrics (i.e., R^2) to more complicated models to characterize how each factor of interest influences EAM predictions. We show these approaches in the results section for both Ft. Benning and Ft. Hood. We did not automate analysis because each researcher or manager is likely to institute his or her own approach, based on highly site-specific needs.

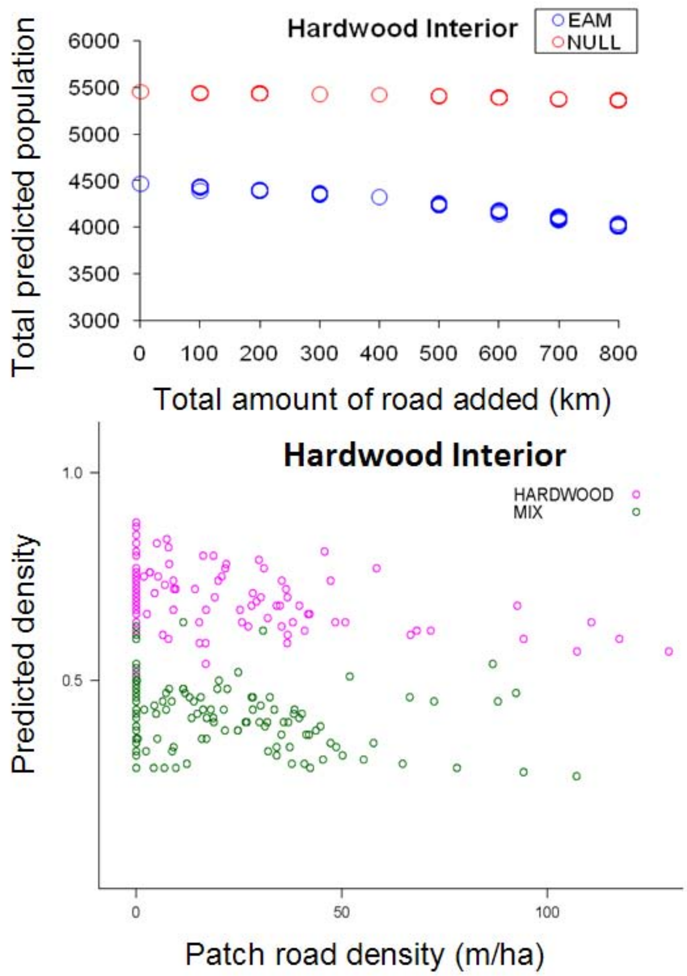


Figure 6. Graphs output automatically by the custom R-package REAM showing landscape scale (a) and patch-level (b) results.

4.6 Step 6: Develop Guidelines and Recommendations

Our scenario sets are for demonstration purposes only, so we are not providing any specific management recommendations based on our modeling efforts. Instead, we show how our outputs could be used to develop management guidelines. We also show how the EAM output could be used to develop general guidelines (i.e., preferential placement of restoration sites near similar habitat) that may be useful to mangers and may even shape how managers think about landscape-scale restoration and habitat management problems.

5. Results and Discussion

5.1. The Revised and Updated EAM

Our new version of the EAM has many features not included in the previous version. A schematic illustrating program flow and new features is shown in Figure 7 and the manual is found in Appendix B.

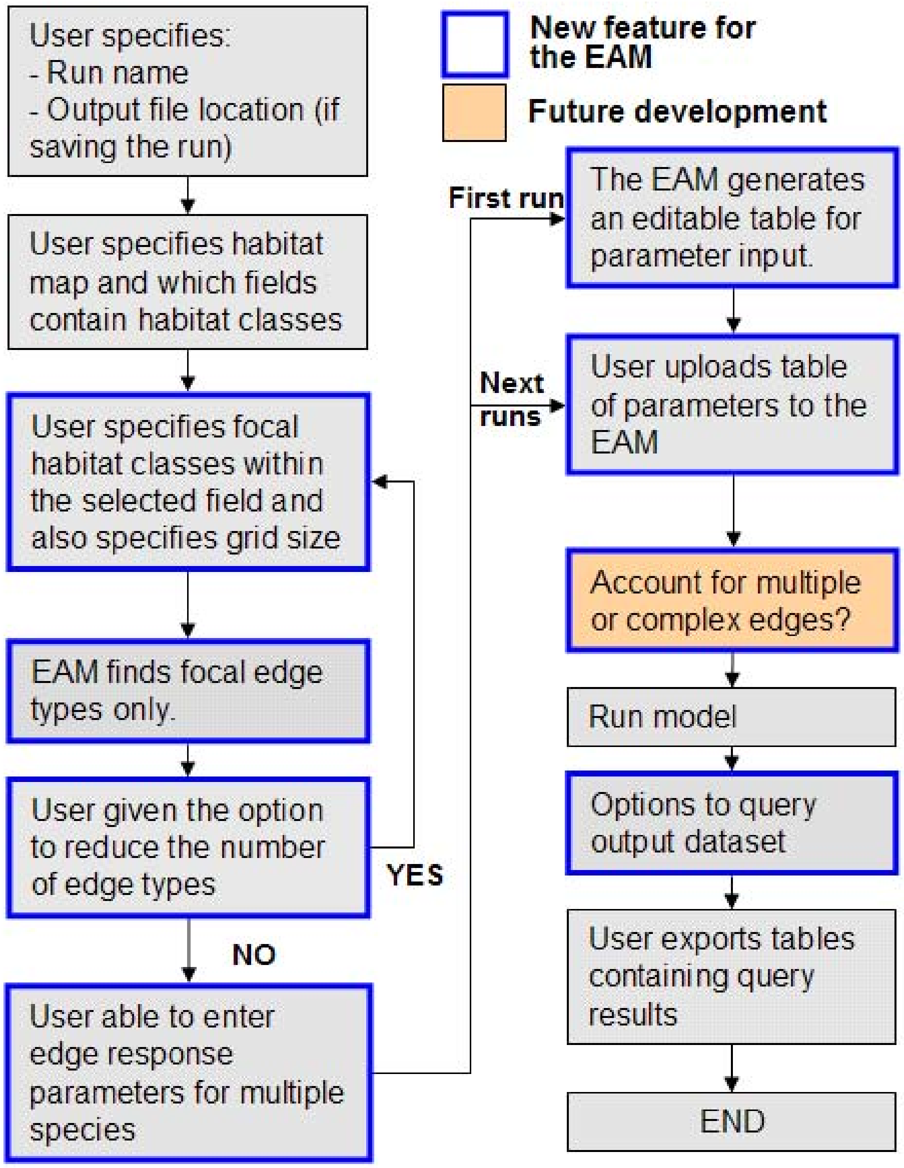


Figure 7. Workflow for the new EAM developed for ArcGIS

In order to simplify use of the model, the new version of the EAM was designed so that the user moves through each step via a series of wizard-like tabs (Fig. 8). Each tab requires the user to enter information, usually by checking boxes. In addition, many tabs display hints that the user can click on for helpful information. Although our original plan was to have the user

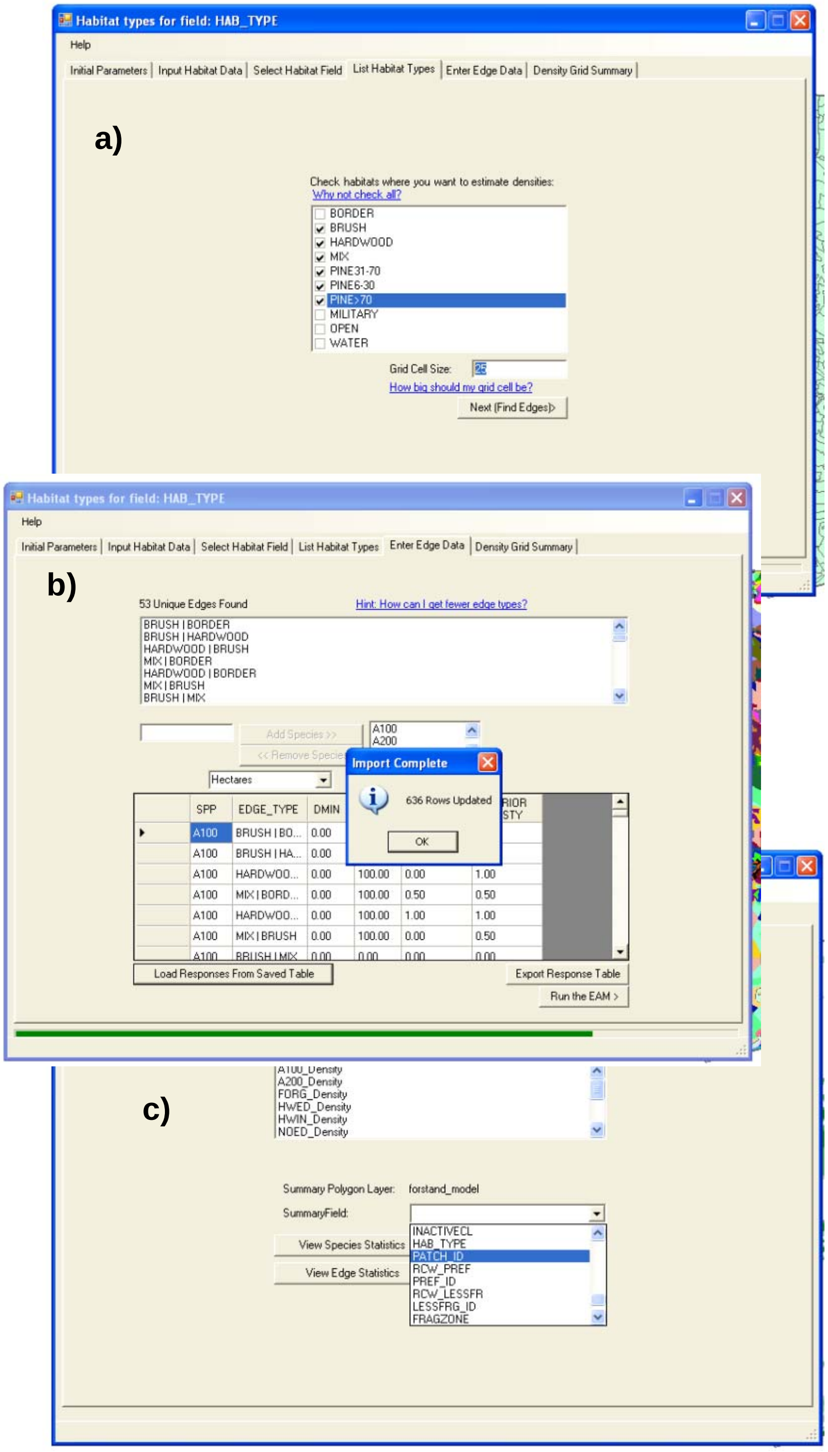


Figure 8. To run the new EAM, the user runs through a series of wizard-like tabs. The final three are shown here, where users check focal habitats (a), enter edge parameters (b), and choose a field to summarize output (c).

able to save runs and then recall them later if they chose to run a different set of parameters, that goal has proven intractable because of data "locks" that the ArcGIS environment maintains on the grids. However, the user is able to automatically save all products into a folder of their choosing, and a map document is also automatically saved so that the same environment can be easily recalled. This version of the EAM is operable in versions 9.2 and 9.3 of ArcGIS. There were substantial differences between 9.1 and the later versions, which would have required significant recoding of the model to insure additional backward compatibility. Since that version is used by only a small and diminishing portion of the user community, we elected not to invest in that recoding. Below, we highlight all the new features of the EAM.

Our new version of the EAM allows the user to restrict the habitat types for which the model calculates edge effects and estimates abundance (Fig. 8a). This has the potential to vastly reduce the number of parameters that must be entered for each species. For example, if a user is modeling landscape-scale patterns in the abundance of forest-restricted species, they might choose to model only forested habitats. Then, instead of the EAM returning a factorial combination of every edge on the landscape (i.e., FOREST|OPEN and OPEN|FOREST, as well as all other combinations), it would return only FOREST|OPEN and other edge types that affect species abundance in forested patches. For landscapes with many habitat classes, the implications of this reduction in parameter estimation are substantial. For instance, at Ft. Hood, if all habitats are chosen, 71 unique edge types are found. However, when choosing the two "focal" habitat types we used in the key scenarios presented in this report, only 16 unique edge types are returned. The impact at Ft. Benning is less dramatic, but only because we model a much larger portion of the installation (all forested habitat), and to reasonably capture important habitat distinctions there, forest is separated into five classes. At Ft. Benning, 87 unique edge types exist on the landscape as we classified it, but only 53 edge types are modeled when we restrict modeling to six focal habitat types. At the tab where users choose focal habitat types (Fig. 8a), there is a "hint" asking "Why not check all?" If the user views this hint, the advantage of choosing fewer focal habitat types is described. Modeling only those habitats of management interest also has the effect of reducing processing time for the EAM because grids are not generated over habitat types that the user does not explicitly identify. Ultimately, the fewer habitat types the user specifies, the faster the input and processing speed.

Because the number of edges scales as a factorial of the number of habitat types, users may not appreciate how many edges are present in their landscape until they implement their first EAM run. At that time, the EAM returns to the user the number of unique edge types (see Fig. 8b). It also gives the user the option to model fewer edge types. There is a clickable "hint" at this point: "How can I get fewer edge types?" If the user clicks this hint, they will be instructed to back up and choose fewer habitat types or exit out of the EAM and pool habitat categories together (i.e., under certain circumstances, HARDWOOD and PINE might appropriately be pooled into a single category called FOREST).

The previous version of the EAM required that data for each species of interest be entered into the EAM separately for each run. Although it was possible to construct one's own database and import the data for each run, this process was extremely time consuming. Not only did the user need to enter or import each species' data separately, but they had to wait through the processing time for each run to allow them to enter in the next species' values. One of the main improvements of the new version of the EAM is the ability to enter data for all species into a table and have the EAM batch through each species, without the need for user input between each model run. The user can either enter data directly into the EAM user-interface table or they can upload parameters from an external table. For purposes of quality control, efficiency and data management, we recommend developing an external table for all but the simplest applications. The first time users run the EAM, they will have the option to enter in codes for all species of interest (see buttons to add species in Fig. 8b; note that in this example the buttons are "grayed out" because the parameters were imported from a file). After entering a code for each focal species, users can generate an editable .csv file (which launches into Excel). This file is saved and then uploaded into the EAM for each run. Further, if the user takes advantage of our REAM package, then this same file becomes one of the key inputs to the species summary table.

Real landscapes are complex with respect to the shape and arrangement of their mosaic of patches. Although most field studies of edge effects attempt to avoid or just ignore features such as patch corners or peninsulas, which may exacerbate edge effects, or the proximity to more than two converging habitat types, which adds complexity to edge response, these features are ubiquitous on most landscapes. Our understanding of their influence on organism distributions is limited because complex landscape geometry has typically been avoided or ignored at the study design stage. Further, there has never been a practical tool for investigating the influence of complex landscape geometry on edge responses. Thus, there is almost no theoretical or empirical work that quantifies how species react to the complex spatial structure of real landscapes, where multiple habitat types often converge in a small area. We have included the first practical implementation of a complex-edge-effects-enabled EAM within our R-package called “edgefx” (Appendix C). However, this feature has not been coded into the ArcGIS implementation of the EAM because we are still exploring whether the increased complexity and processing time that it would require is justified by improved predictive power. Our preliminary application, primarily a research tool at present, incorporates complex edge geometry on a simple binary (i.e. habitat/non-habitat) landscape. We detail the progress we’ve made in developing models to measure and quantify complex and multiple edge effects in the field in section 5.2.

The primary outputs of the EAM are the density grids that are generated for each species input for each model run. Any ArcGIS user who is comfortable with the analytical functions for grids in the ArcGIS environment can use the output density grids as they would any other raster data set. However, most users will want a standard summary of the grid values based on one or more attribute fields in the original map (i.e., individual patches, habitat types, or land-use classes). The EAM provides a summary of the grids sorted on any field the user chooses. These density grid summaries were available in the original version of the EAM, but a new feature generates summaries of the landscape structure detailed in each map. This allows the user to easily extract patch statistics that can help determine critical metrics for their landscape. These metrics include the number of edge types, the area of each patch that is closest to each particular edge type, and the mean distance to the nearest edge, for each unit in the modeled landscape. These and other descriptive statistics may be informative in themselves, and they provide avenues for analyzing patterns in the abundance data generated by each model run.

Release Notes

As each new feature of the EAM was launched, it was tested and approved (by Leslie Ries and technicians) before moving on to other elements of the EAM. However, an unanticipated change in programmers late in this project has delayed release of the revised EAM to the public; thus, beta testing is occurring at the end of this project, rather than midstream. We plan to respond to user-identified problems as we receive them, and will also keep track of subsequent feedback and incorporate any suggested revisions into future versions of the EAM.

The model has been implemented and tested on both ArcGIS 9.2 and 9.3 platforms and produce nearly identical results. For patch statistics, of 561 individual results returned, there were four differences between the 9.2 and 9.3 version (0.7%). In those cases, area estimates differed from 0.001 to 0.0005 ha and are therefore trivial. A similar result was found for population estimates. Eight out of 626 results (1.3%) came back with population predictions that differed from 0.001 to 0.0000001 individuals in an entire population. Research by our technician (Jared Andre of Iron Rim) suggested that slight differences between the 9.2 and 9.3 ArcGIS platforms could explain these minor differences in output.

5.2. Measuring Edge Responses to Capture Complex Effects

The best approach to measuring edge responses has been a topic that has received a great deal of attention in the edge literature (Ries et al. 2004) and has been something that our group has grappled with in the past. The most common topic of debate has been the best way to capture the non-linear dynamics that result from the threshold nature of edge effects. By this we mean that edge effects are expected to extend only a limited distance into habitat, thereafter leveling off at a characteristic distance that is associated with the "core" of the habitat patch. Several approaches have been proposed (Fraver 1994, Cadenasso et al. 1997, Laurance et al. 1998, Mancke and Gavin 2000, Brand and George 2001, Harper and MacDonald 2001, Toms and Lesperance 2003, Ewers and Didham 2006), although none has become commonly used. Further, none of these models address the critical assumption of most edge studies - that the best metric for describing edge effects is the distance to the closest edge. This assumption allows researchers to ignore both complex edge geometry (Fig. 9a,b) and the presence of multiple adjoining habitat types (Fig. 9c). In some cases, researchers studying edges attempt to set up transects along the straightest, most "ideal" edges (Fig. 10a), far from converging edge types. More commonly, nothing about edge geometry is noted in the study design, so we assume that the issue is entirely ignored. In either case, both force an assumption of "ideal" edge geometry. This critical assumption is problematic, however, when seeking to extrapolate edges over landscapes, which typically have complex geometries and multiple, converging edge types (Fig. 10b,c).

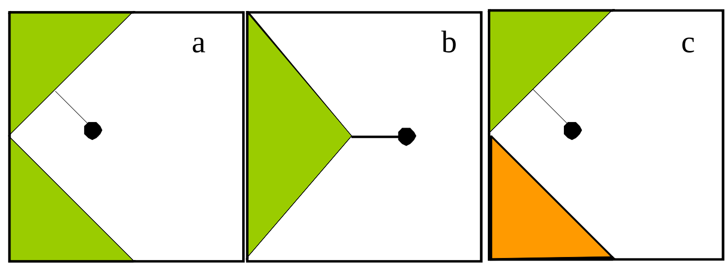


Figure 9. Complex and multiple edge effects. Edge influence may be strengthened (a) or lessened (b) depending on edge geometry. How responses interact when three habitat types intersect (c) is unknown.

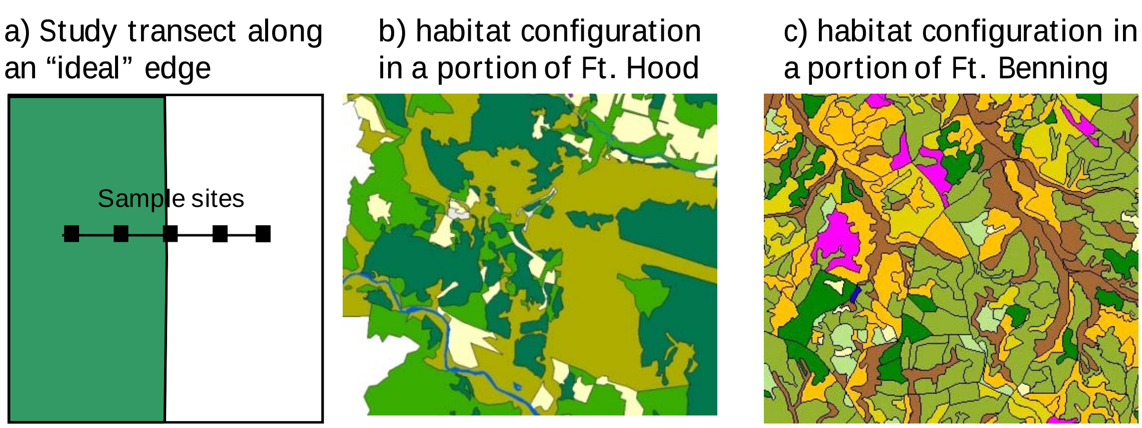


Figure 10. Most edge studies seek out simple landscapes in which to measure edge effects (a), but then may not reasonably be used to extrapolate responses over real landscapes such as those found at Ft. Hood (b) and Ft. Benning (c).

There have been very few studies that have explored the implications of complex edge geometry. The most thorough to date have shown that edge effects are intensified in corners (Fletcher 2005) and corridors (Harper et al. 2007) and incorporating complex geometries into landscape-level extrapolations has minor, but measurable impacts (Fletcher 2005). Surprisingly, of the hundreds of edge studies published in the past several decades, none have empirically measured the influence of the convergence of multiple habitat types, although one study showed how these effects could be approached mathematically (Fernandez et al. 2002). This, despite the fact that a recent study showed up to 60% of a landscape is within 120m of a convergence point between three or more habitat types (Li et al. 2007). Despite this dearth of knowledge, we must confront these implications because our model takes local edge responses and extrapolates them over entire landscapes potentially multiplying errors of overly simplistic assumptions regarding landscape structure. Real landscapes are invariably filled with complex shapes and the convergence of multiple habitat types (Fig. 10b,c). Currently, the EAM uses the distance to the closest edge as the key measure of edge effects. However, we have begun to explore the best approach to considering complex geometry, the impact it may have on our predictions, and determining how these calculations could or should be incorporated into future versions of the EAM.

Malcolm's Model of Complex Geometry

Malcolm (1994) developed a model that we believe offers the best framework both for determining the distance of maximum edge influence and dealing with the issue of complex edge geometry. Malcolm's model has been cited numerous times (139 as of Jan 2010), but we found no evidence that it has ever been implemented (beyond the original publication). The model's solution was useful in that it can incorporate actual patch geometry and also results in a non-linear solution with the exact type of threshold effect that has been sought by many in the past. Further, this modeling approach allows complex geometry to be factored in either when measuring edge effects in the field or when predicting edge influence throughout a landscape. Ultimately, Malcolm's solution is useful because it returns parameters that are of interest to most researchers: estimates in the habitat core (k), the maximum distance of edge influence (Dmax), and a parameter describing the effect of the edge (e0). We can only speculate as to why such a useful model has never been applied (beyond the original paper) over a 15 year period, but we suspect that at least part is due to the mathematical complexity of applying the model in real landscapes.

The basic model considers that every point along an edge can exert an ecological influence (say on animal density or plant height) on any point in space, up to some maximum distance (Fig. 11). In Malcolm's original model this point edge effect was assumed to be linear from the edge to the maximum distance of edge influence (Dmax), at which point it was assumed to level off (Fig. 11a). We have extended this model to allow plateaus at both the edge and the interior (Fig. 11b) by adding an additional parameter, Do. Point effects are integrated across the entire edge at all distances less than Dmax to arrive at a predicted density (or plant height, etc.) at any point in space, as long as the configuration of all edges within the specified distance are known. In the original paper, the only solution presented was for a point along an "ideal" edge that is perfectly straight, divides two habitats only, and extends to infinity in both directions (Fig. 12a). However, the model was intended to be used in more complex patch shapes, and Malcolm (1994) noted that the model could be used on patches of *any* shape. To do this, Malcolm

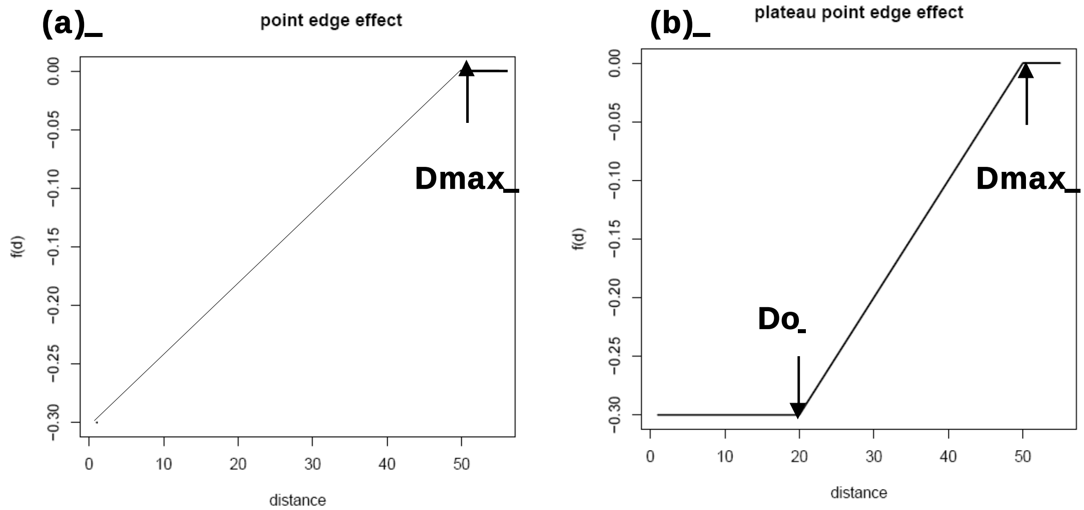


Figure 11. Malcolm's model uses a point edge effect that is a function of distance. The original model allowed a plateau only at Dmax (a), but has now been extended to allow a plateau at the edge via the parameter Do.

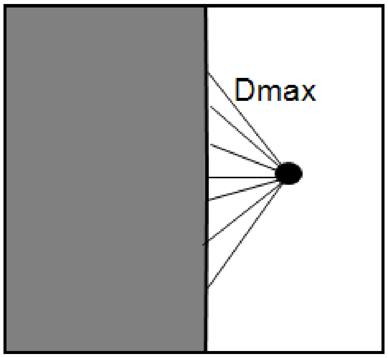
suggested dividing the patch into straight- line segments, and then adjusting the limits of integration accordingly. We did this for a simple, "ideal" corner (meaning that it is exactly 90^o and extends past Dmax in both directions). The solution is shown in Fig. 12b and gives an indication of why this model has never been implemented in real landscapes. This solution is only applicable to a perfect corner and even a corner of slightly different geometry (e.g., 89^o) would require a different solution. In reality, a unique solution is required for every patch in a typical landscape (except, perhaps, experimental landscapes). Obviously, the task of individually finding a unique solution to every patch on the landscape is intractable. This presented us with the dual challenges of applying this model on our real landscapes and also developing a method that makes it approachable for others to do so.

To tackle both challenges, we developed an R package ("edgefx") that, given a simple map of all edges within Dmax, calculates the solution and allows parameterization of and predictions generated from Malcolm's model (Appendix C). Further, we implemented our four-parameter version of Malcolm's original equation along "ideal" edges within the package. This function is useful because many edge studies establish transects along these types of edges (or simply assume they are "ideal"). The "edgefx" package also implements a simplified version of the EAM on a binary landscape to determine the effects of extrapolating edge effects where the complex geometry of the landscape is incorporated into the predictions, rather than considering only the distance to the closest edge (as the EAM currently implemented in ArcGIS does). The R package is written for R version 10.1 or later, and the manual (or "vignette") is included as Appendix C. We used the extensive bird survey network on Ft. Hood to determine how using Malcolm's model influenced the measurement and prediction of edge responses.

Testing Malcolm's Model at Ft. Hood

Our two main goals in testing Malcolm's model were to 1) determine its current usefulness in developing parameters for the EAM and 2) determine whether EAM

(a) "ideal" edge

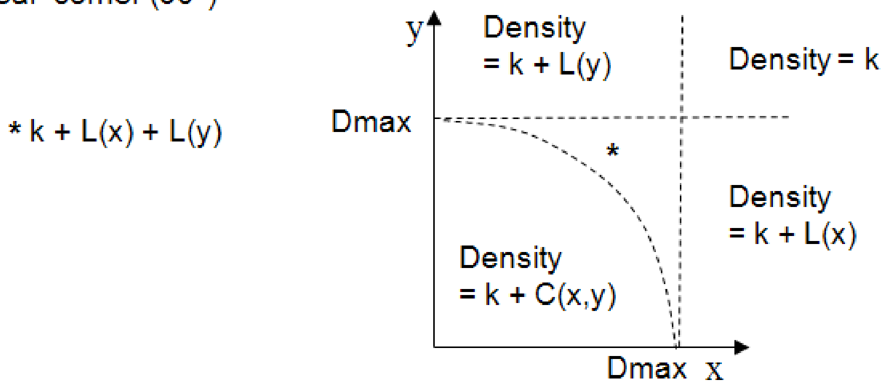


$$Density = k + L(D)$$

$$Where\ D < Dmax,\ else\ k$$

$$L(D) = e_0\left[\sqrt{D\max - D^2} + \frac{D^2}{2D\max}\ln\left(\frac{D\max - \sqrt{D\max - D^2}}{D\max + \sqrt{D\max - D^2}}\right)\right]$$

(b) "ideal" corner (90°)



Where:

$$\begin{aligned} C(x,y) &= \int_0^{x+\sqrt{D_{max}^2-y^2}} e_0\left(1-\frac{\sqrt{y^2+(t_x-x)^2}}{D_{max}}\right)dt_x + \int_0^{y+\sqrt{D_{max}^2-x^2}} e_0\left(1-\frac{\sqrt{x^2+(t_y-y)^2}}{D_{max}}\right)dt_y \\ &= e_0\left[\frac{1}{2}\sqrt{D_{max}^2-x^2}+\frac{1}{2}\sqrt{D_{max}^2-y^2}+(x+y)\left(1-\frac{\sqrt{x^2+y^2}}{2D_{max}}\right)\right. \\ &\quad \left.+\frac{x^2}{2D_{max}}\ln\left(\frac{\sqrt{x^2+y^2}-y}{D_{max}+\sqrt{D_{max}^2-x^2}}\right)+\frac{y^2}{2D_{max}}\ln\left(\frac{\sqrt{x^2+y^2}-x}{D_{max}+\sqrt{D_{max}^2-y^2}}\right)\right] \end{aligned}$$

Figure 12. The solution to Malcolm's model for the two simplest geometries within a landscape: along a perfectly straight ("ideal") edge that extends past Dmax in both directions (a) and a perfect ("ideal") 90° corner that extends past Dmax in both directions (b).

implementation incorporating complex geometry could improve predictions of edge effects across complex landscapes. To do this, we compared four models: Malcolm's complex edge model (COMPLEX), a simplification of Malcolm's model assuming an "ideal" edge (IDEAL), a traditional model that uses only distance to the nearest edge (DNE) and a null model that ignored edge influences entirely (NULL). The value of implementing the IDEAL simplification of Malcolm's model lies in its assumption of "ideal" geometry, thus it requires only information on distance to the closest edge (rather than detailed patch geometry maps), yet it still returns the critical parameters Dmax, k, e0 and, now, Do (Fig. 11b), parameters that are of interest to most managers and researchers. Further, these parallel the parameters currently used for the EAM.

We built the four models from data drawn from the 638 points in Ft. Hood's bird survey network (Fig. 4a) that are along the straightest (in other words, most "ideal") edges. We then used the parameters derived from these points to predict densities near edges with the most complex geometries. We were then able to compare densities observed near those complex edges with predictions from the four models to see which model's predictions were closest to the observed values. This is the first test of Malcolm's model that we are aware of in a complex landscape (Malcolm's original 1994 paper tested the model in square patches).

It should be noted that the bird survey program at Ft. Hood was in no way designed to measure edge responses. However, because of the large number of survey points in Ft. Hood's network, points coincidentally occur at various distances from many different edge types, but are scattered haphazardly across the base. Obviously, we could not formally control for any aspect of edge geometry. Ideally, points would be set up along transects at varying distances from each edge of interest (as in Fig. 10a), reducing variability due to local effects. Further, Ft. Hood surveys are conducted so that birds are counted up to 50m from each point, meaning that we were unable to use data from any point closer than 50m from an edge. This eliminated surveys in the closest edge zones where edge effects are strongest (see Fig. 11). Data from 2002-2005 were used because all survey routes had been set up by 2002, but methodology was radically changed in 2006 in SCRUB habitat, making comparisons after 2005 impossible. Analyses were performed on each year (2002 through 2005) as well as on mean densities from all four years combined.

We used data from nine bird species, including those that prefer WOOD habitat (the GCWA's main habitat type), SCRUB habitat (the BCVI's main habitat type), and also a set of species that are found in both (Fig. 13). We focused on four edge types: WOOD|OPEN, WOOD|SCRUB, WOOD|SCTREES AND SCRUB|WOOD. We also used Malcolm's model to fit responses at road edges, but because roads were largely straight, there was not an opportunity to test the model on roads with complex geometries, so we omit those results here. However, we present them in the section 5.5 on parameterizing edge responses for the EAM at Ft. Hood. As always, we began the analytical process by developing predictions for edge responses we

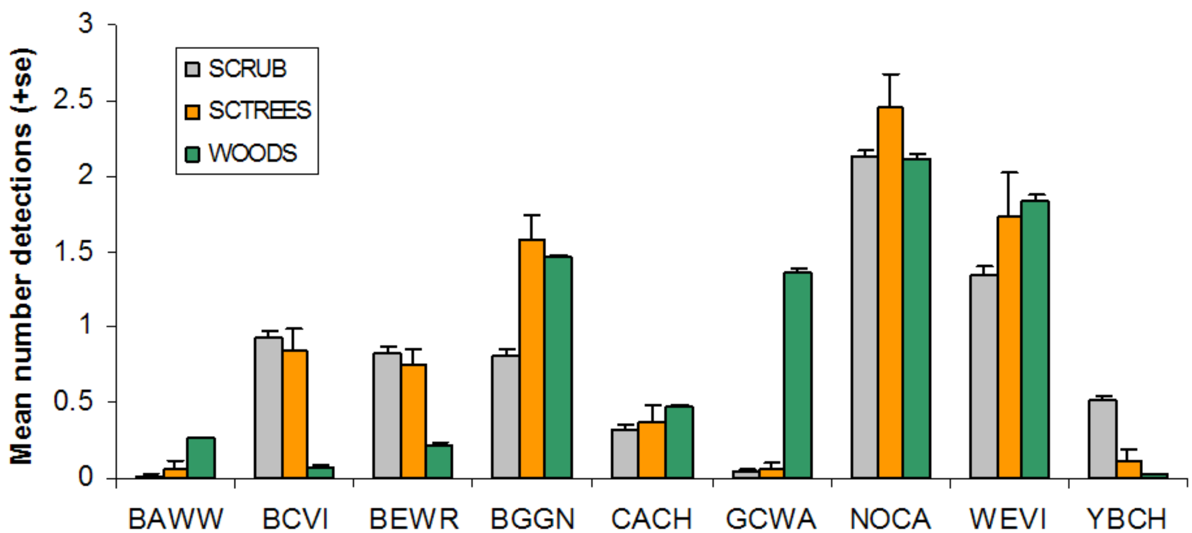


Figure 13. The habitat associations of nine common species on Ft. Hood relative to three main habitat types. Full species names are shown in the acronym list (page iv of this report).

expected to see for each species based on our edge response model (Fig. 1c). This approach allows us to make better sense of the results and to continue to refine our model. We did not use published results from other studies to make our predictions, but it is worth noting that several of the species have been shown to show edge responses in other studies. For instance, the GCWA has been shown to have lower fecundity at edges (Peak 2007) and are also known to be area sensitive (Ladd and Gass 1999). In general, species associated with scrub are thought to prefer edges, but recent reanalysis shows that this is only in reference to forest interiors and if compared to the interiors of their preferred habitat, these species often avoid edges (Schlossberg and King 2008).

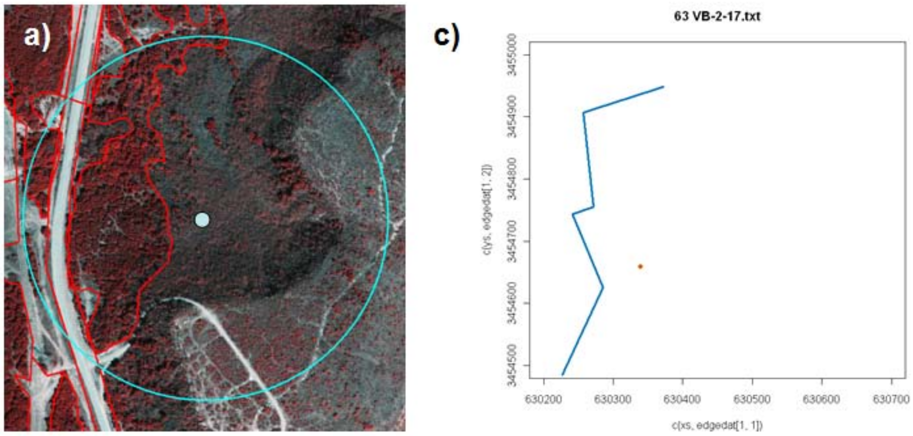
For all species, there is a great deal of scatter in the data, as was expected due to the distribution of points throughout the landscape. Of the nine species, four showed the most consistent edge responses, and always in the predicted direction (Table 1). Because our main goal here is to test Malcolm's model, we restrict the presentation and discussion of results to four species: golden-cheeked warblers (GCWA), black-capped vireos (BCVI), black-and-white warbler (BAWW), and bewick's wrens (BEWR). GCWA and BAWW are associated primarily with the oldest WOOD habitat and BCVI and BEWR are associated with SCRUB and SCTREE habitat (Fig. 13).

Table 1. Edge response predictions and results for nine bird species on Ft. Hood.

Species	Edge	Prediction*	Result
Golden-cheeked warbler	Wood|All	Neg	Generally Neg, some NR
Black-capped vireo	Scrub|Wood	Neg	Generally Neg, some NR
Black-and-white warbler	Wood|All	Neg	Some Neg, some NR
Bewick's Wren	Scrub|Wood	Neg	Generally Neg, some NR
Blue-gray gnatcatcher	Woods and Scrub edges	NR	NR
Carolina chickadee	Woods and Scrub edges	NR	NR
Northern cardinal	Woods and Scrub edges	Pos/NR at several edges	Mostly NR, one neg
White-eyed vireo	Wood and scrub edges	NR	NR
Yellow-breasted chat	Scrub|All	Neg	NR, but some neg trends

*Neg= negative edge response, NR = no edge response, Pos = positive edge response

In order to develop parameters for our four competing models (NULL, DNE, IDEAL, COMPLEX), we went through several steps that allowed us to classify each point among Ft. Hood's network of 638 point count stations. All classifications were made using false-color remotely-sensed satellite imagery with 1 m resolution (Fig. 14a). Our model allowed us to deal with complex geometry, but not converging edges of multiple habitat types, so we were constrained to look for points with only one edge type within a specified distance. First, we arbitrarily set a preliminary tolerance of 500m to allow initial exploration of basic patterns. This is a very conservative distance since most reported bird Dmaxes are on the order of 100-200m (Laurance 2008). Based on this, we found a small number of points with relatively straight edges and no multiple edges within that large radius. Based on this small number of points, we did some preliminary analyses (not shown) that suggested edge responses were generally occurring on the scale of 200-300m. Therefore, we reset our cut-off and identified points among Ft. Hood's bird survey network along the four edge types with each focal edge type only within



b)

```
630339,3454659, , ,#Point VB-2-17
630372.647,3454948.064,630256.760,3454906.789,ScrubVI|WoodsWA
630256.760,3454906.789,630271.120,3454754.802,ScrubVI|WoodsWA
630271.120,3454754.802,630240.885,3454743.276,ScrubVI|WoodsWA
630240.885,3454743.276,630284.936,3454625.554,ScrubVI|WoodsWA
630284.936,3454625.554,630226.301,3454485.160,ScrubVI|WoodsWA
```

Figure 14. Geometry from satellite imagery of a survey point in SCRUB bordering WOODS (a) is converted into line segments and input into R via text files (b). The segments visualized in R output (c).

300m. Necessity forced us to allow similar edges between 200-300m (otherwise we would not have been able to find a sufficient number of points for analysis). Beyond 300m, we ignored multiple edges and complex edge geometry but still recorded the distance to and type of the closest edge. Only points within 500m of a focal edge were used.

We then separated all points into two groups: model building points (which we used to develop parameters for our four models) and model testing points (which we used to test the predictions of each model). The model-building points were along edges that were the straightest (when the nearest point was within 200m) or any points were the nearest edge was beyond 200m. Model testing points were those with the most convoluted edges within 200m. The following list shows the final number of points designated for each edge type.

WOODS|OPEN: 38 (BUILD), 15 (TEST)
WOODS|SCRUB: 26 (BUILD), 8 (TEST)
WOODS|SCTREES: 41 (BUILD), 15 (TEST)
SCRUB|WOODS: 22 (BUILD), 13 (TEST)

We developed parameters for the four models as follows. For the DNE model, we used ordinary linear regression. Although some DNE methods have been developed to detect plateaus (i.e., Toms and Lesperence 2003), in reality they are rarely implemented, so this approach represents what is likely the most common analytical approach to measure edge effects. For the IDEAL model, we used a custom function (infinite.edge.effect) in our "edgefx" R-package (see

Appendix C). This model assumes that all edges are straight and extend to infinity in both directions. For the COMPLEX model, we used a custom function (edge.nls) in our "edgefx" R-package which optimizes the four (or, optionally, only Malcolm's original three) parameters by considering actual edge geometry (Appendix C). Edge geometry is supplied for each point via a text file that has the x,y coordinates of the survey point and the start and stop point of each edge segment within our pre-determined cutoff of 300m radius (Fig. 14). An example of imagery of a survey point, the text file, and the resulting edge map that R uses as input are provided in Fig. 14. Finally, we use interior densities (k) predicted by Malcolm's model for the NULL model. The reason we use interior (rather than mean) densities is because the traditional approach to habitat studies is to set up survey sites sufficiently far enough from edges so that their effects can be ignored. Since both the IDEAL and COMPLEX models return estimates for k, we needed to choose between the two values. To do this, we used an information-theoretic approach and chose the model with the lowest Akaike Information Criterion (AIC) score (Burnham and Anderson 1998).

Because the IDEAL and COMPLEX models are non-linear, fitting them requires supplying the procedure with starting parameters. To get initial parameters, we visually inspected graphs showing densities for each species at each edge type in each year. If no edge gradient was obvious in the graph, models were not run for that species/edge type/year combination. Where even a slight pattern was evident, we developed initial guesses as follows: Do was set to 0, Dmax was set to 200m, and e0 was set to 0.001 (positive or negative depending on whether the observed edge response gradient was positive or negative). Finally, k was set to 0.5, 1 ,or 1.5 based on visual inspection. Based on our initial results, model convergence was rare for the 4 parameter model (and was never chosen by AIC) and model convergence was sensitive to starting parameters. Therefore, after examining initial results and narrowing our focus to four target species, we performed an informal sensitivity analysis using the three parameter model (Malcolm 1994). To conduct this sensitivity analysis, we developed a factorial set of starting parameters for Dmax, k and e0. These parameters encompassed the range of possible Dmax distances based on our point count network (0m, 300m, 500m), densities based on the range of densities observed in the data (0, 1, 2 detections per survey), and a three-order-of-magnitude range for e0 (0.01, 0.001, 0.0001). This factorial design resulted in a set of 27 starting parameters that we used for fitting both the IDEAL and COMPLEX models for each species/edgetype/year combination.

The models with the lowest AIC scores are shown in Table 1. But our results show that when data are highly variable (as is the case on Ft. Hood), the models are highly sensitive to starting parameters. Both IDEAL and COMPLEX models often converged on multiple sets of parameters, and in many cases AIC did not support a single top model (based on a conventional threshold delta AIC value of two). However, this was not true for all models, especially those with the clearest edge patterns. Further, models sometimes converged with Dmax values far in excess of 500m (the maximum value of distance to the nearest edge within our data). These results could be interpreted to mean that there is no statistical support that interior densities have been reached. These results highlight one of the key challenges of designing edge response studies – until you have preliminary results suggesting actual Dmax, it is difficult to develop an appropriate study design. Indeed, Laurance (2004) suggested that many edge studies fail to find edge responses because they are not conducted at the proper scale. Further, our results suggest that when data are variable (as is usually the case in any habitat study), then a strong study design with high replication is necessary. We were fortunate to have so many points to work

Table 2. Parameters from three competing models to measure edge effects (DNC, INFINITE, COMPLEX) will be compared to a NULL model. The models with the lowest AIC score indicates the "best" model based on data fit and number of parameters.

		DNE			IDEAL EDGE				COMPLEX EDGES		
Edge Type	Year	slope	int	AIC	e0	Dmax	k	AIC	e0	Dmax	k
Golden-cheeked warbler (GCWA)											
WOODS|OPEN	Mean	0.002**	0.244	54.05	-0.0032	242**	0.91***	56.23	-0.0028**	314***	1.04***
WOODS|SCRUB	Mean	0.001	0.726**	38.86	-0.0044	208**	1.08***	37.36	-0.005	203**	1.08***
WOODS|SCTREES	Mean	0.006'	0.54*	63.39	-0.0014	460'	1.24**	65.18	-0.0014	402*	1.14***
Black-capped vireo (BCVI)											
SCRUB|WOODS	2003	0.003	0.444	59.75	-0.0076	149	1.21**	60.72	-0.0031	281*	1.35**
Black-and-white warbler (BAWW)											
WOODS|OPEN	2005	0.0006	0.228	59.47	-0.0033	174	0.42***	60.30	-0.0025	195*	0.45***
WOODS|SCRUB	Mean	0.0002	0.175	-1.29	-0.0052	93	0.23***	-0.49	-0.0026	128	0.23***
WOODS|SCTREES	Mean	0.0002	0.179	-0.36	-0.0031	151	0.27***	-0.63	-0.0035	135**	0.26***
Bewick's wren (BEWR)											
SCRUB|WOODS	Mean	0.0027**	0.0113	20.39	-0.0022**	370	0.94	22.42	-0.0016**	553***	1.08***

'$p<0.10$, *$p<0.05$, **$p<0.01$, ***$p<0.0001$

with at Ft. Hood to mitigate some of these problems, but because their network of sampling points was not designed specifically to measure complex edge responses, this limits our inference and weakens our results.

To deal with the problem of multiple, converging models we chose the model with the greatest support (lowest AIC score) for both IDEAL and COMPLEX models. Here, we only present results from a single year of data (or all years combined), depending on which set had the strongest patterns. However, most species showed similar responses from year to year, thus mean values from all years are presented in most cases. Parameters for all four models, along with AIC scores, are shown for each of the four species at the four edge types where they are sufficiently common for analysis (Table 2). Patterns and model fits for the four models are shown for the two main species of management concern at Ft. Hood, the GCWA and BCVI (Fig. 15) and for two additional habitat-specific species, the BAWW and BEWR (Fig. 16). The fit for

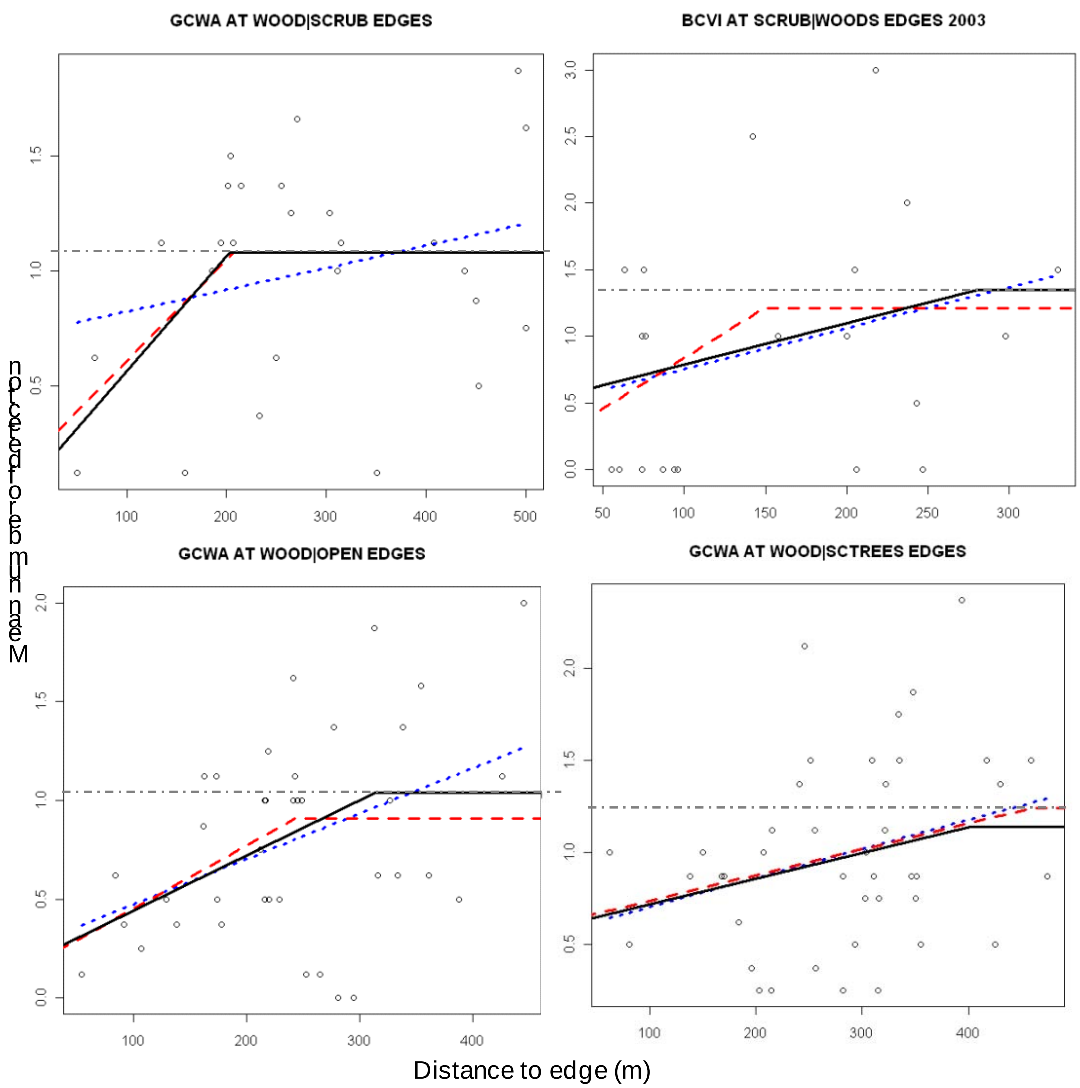


Figure 15. Edge responses for the two species of critical management concern (GCWA and BCVI) at Ft. Hood and the best fit lines from four competing models: COMPLEX (solid, black line), IDEAL (red, dashed line), DNE (blue, dotted line), NULL (grey dot-dash line).

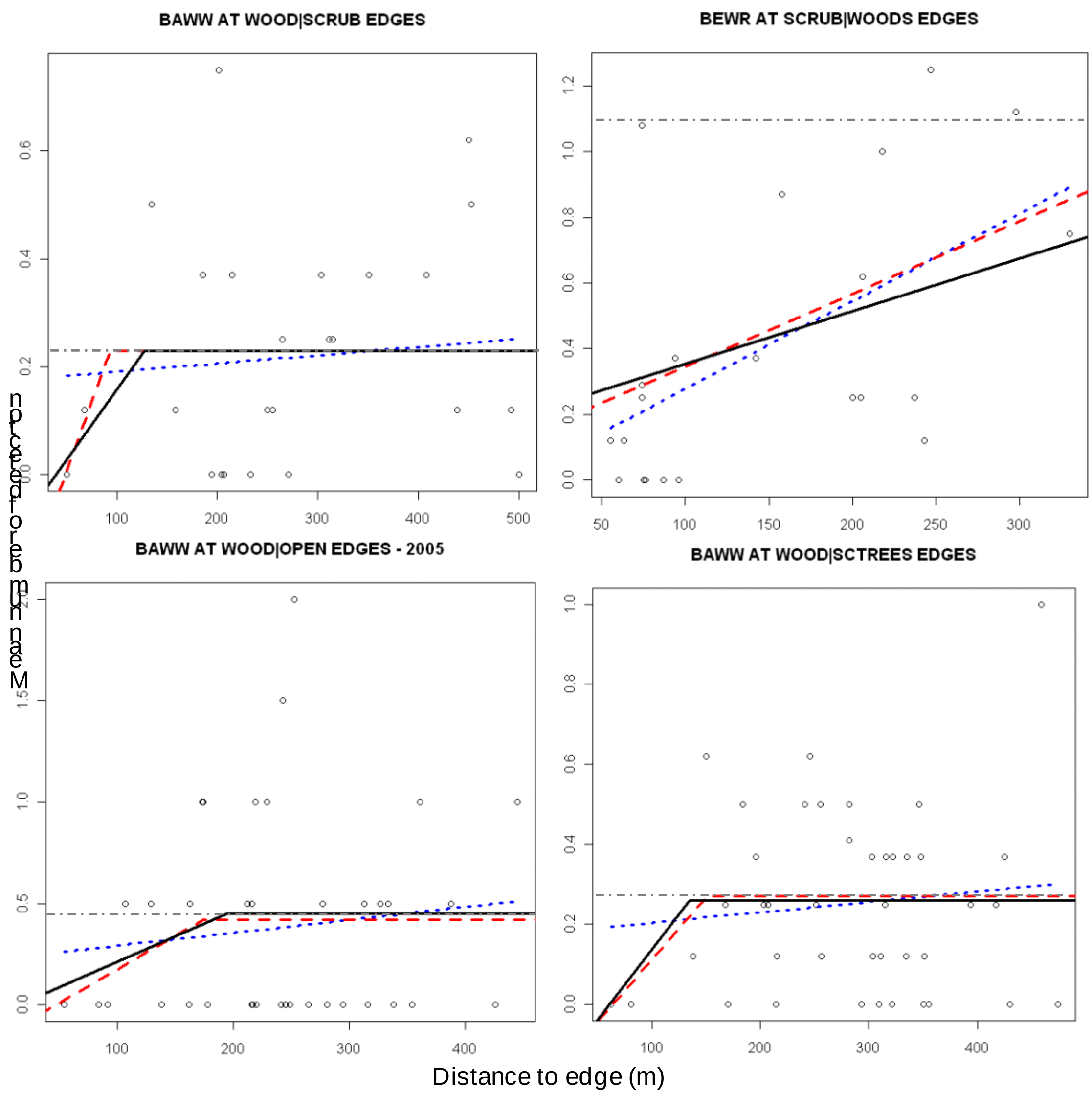


Figure 16. Edge responses for two additional species (BAWW and BEWR) at Ft. Hood and the best fit lines from four competing models: COMPLEX (solid, black line), IDEAL (red, dashed line), DNE (blue, dotted line), NULL (grey dot-dash line).

the COMPLEX model is included for comparison purposes only, but since it is not based on the distance to closest edge, its fit can not fairly be judged visually by this display. Note that models often predict similar patterns, but may differ depending on whether and where thresholds are reached. Note that when Dmax is beyond 500m, both IDEAL and COMPLEX models are linear within the range of data collection (i.e., BEWR in Fig. 16). The model with the best fit, based on AIC score, is highlighted in Table 2 for comparison purposes only. We do not choose among the four models based on AIC, but instead based on which model does the best job predicting density values at our TEST points that are characterized by convoluted geometry.

Comparison of Observations to Predictions

In order to test the four competing models (NULL, DNE, IDEAL, COMPLEX) against field data, independent test points were identified separately from the points used to build parameters for the four models. We then used parameters from the four competing models (Table 2) to generate predicted densities for each of the test points. Those predicted densities were then compared to observations that had been measured in the field by technicians at Ft. Hood. To generate actual predictions from these parameters, we followed fixed procedures for each model's output. The NULL predictions remained constant for each species at each edge type. For DNE and IDEAL predictions, we simply plugged the parameter values into the model equations to generate values for comparison. For the COMPLEX model, we had developed a function in the "edgefx" R-package (Appendix C) called "map.edge.effect," which applies the parameters given to the edge segments of a vector map (illustrated in Fig. 14) and implements Malcolm's model.

It is important to note that the deviation of COMPLEX predictions from an "idealized" realization of the same parameter set (i.e., if we used the parameters built from points where edge geometry was accounted for, but assumed that all the test survey points were along edges that are "ideal") shows the impact of including actual edge geometry in the implementation of Malcolm's model (Fig. 17). The magnitude of these deviations will vary depending on both the values in the parameter set and the shape of the

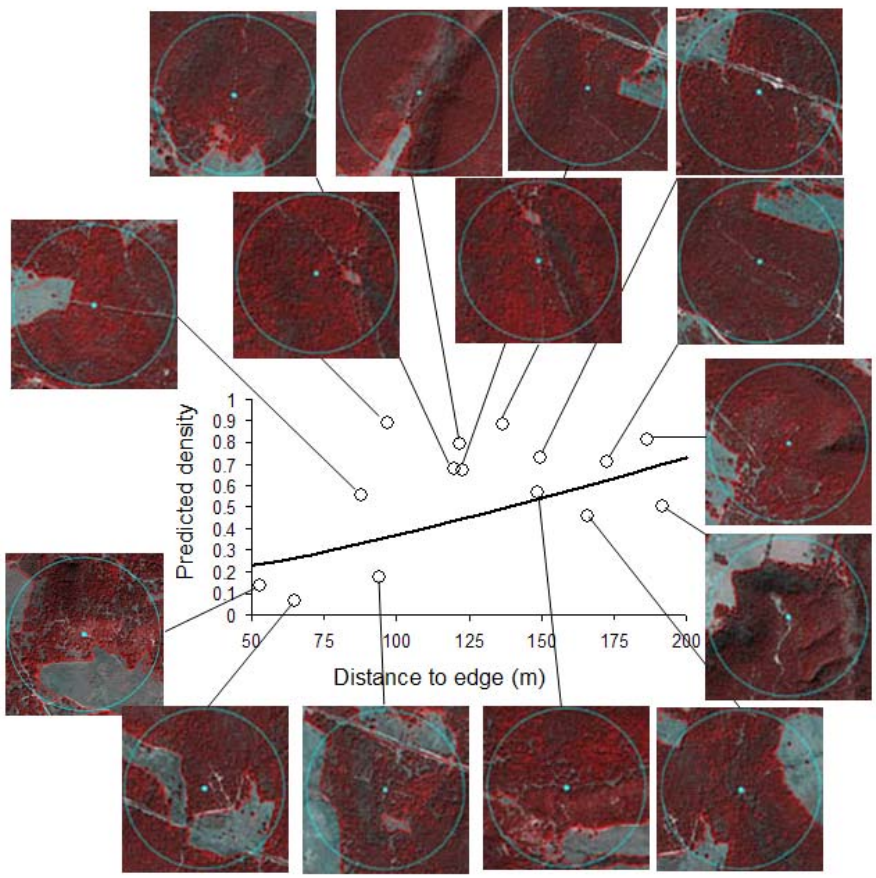


Figure 17. Deviation of predictions from Malcolm's model when parameters are implemented assuming that each point has ideal geometry (straight line) and when actual edge geometry is accounted for (circles). Each point represents a different point count location and remote imagery for each point is provided so that predicted deviations can be compared to actual edge geometry.

edges near each sampling point. We illustrate the magnitude of these deviations for the GCWA at the 15 WOODS-OPEN test points (Fig. 17). This example shows that the magnitude of the difference in prediction can be quite substantial. It is also a reminder that the scatter of observations relative to distance to closest edge (as illustrated in Figs. 15 and 16) can give a misleading view of how important edges are in shaping ecological patterns. For instance, most edge studies fail to find a significant pattern (Ries and Sisk, *in press*), yet these studies never take edge geometry into account and rarely state to what extent edge geometry was "controlled" for (i.e., by seeking out straight edges with consistent adjacent habitat).

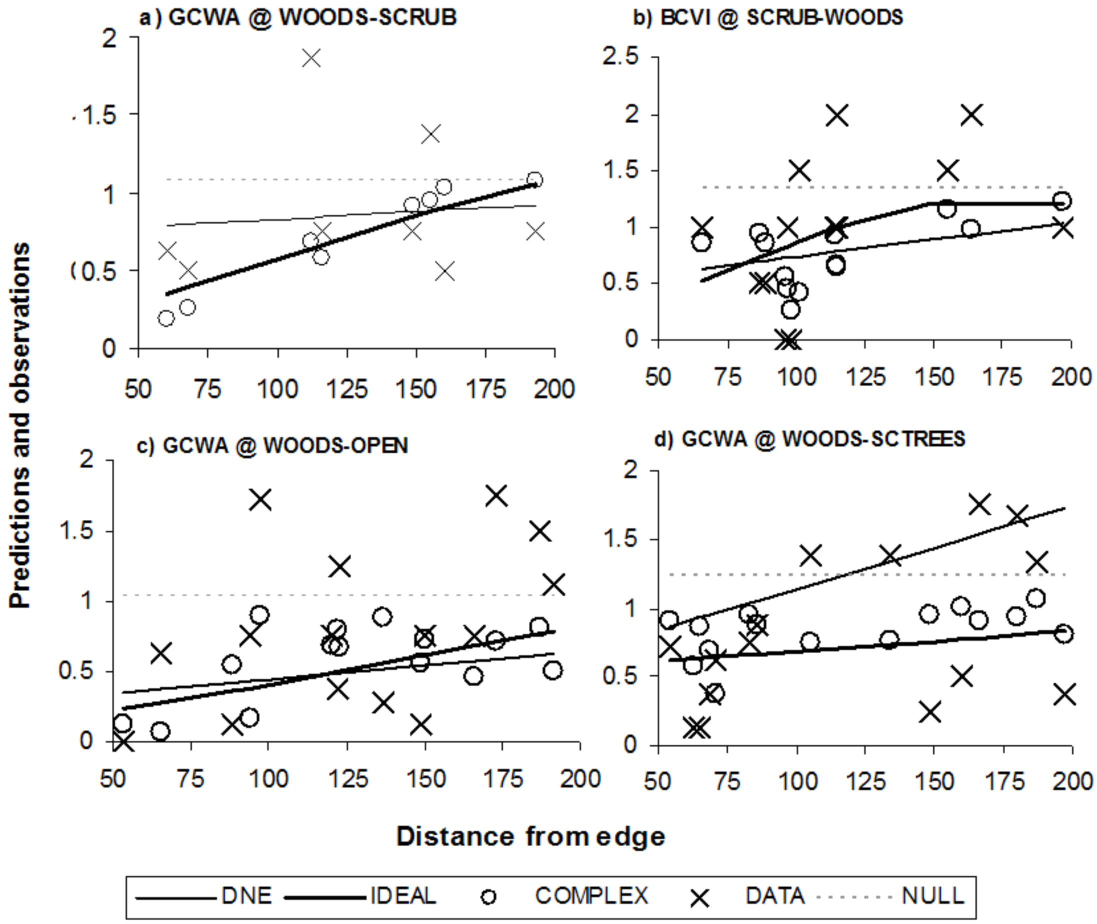


Figure 18. The predictions of four competing models (DNE, IDEAL, COMPLEX, and NULL) are compared to field observations (X's) for the two focal species, GCWA and BCVI, on Ft. Hood at multiple edge types.

The comparisons of observations to the predictions of the four models are illustrated in Fig. 18 for GCWA and BCVI and Fig. 19 for BAWW and BEWR. In almost all cases, the magnitude of variability seen in field observations swamps that predicted by the models, even the predictions of the COMPLEX model. Despite this, it is obvious from these figures that edge responses are also evident in these data sets that are independent of those used for parameter development. In almost all cases, lower densities are observed near the edge compared to further from the edge. The amount of scatter predicted by the COMPLEX model also differs among cases. In some cases, taking edge geometry into account provides substantial difference from the

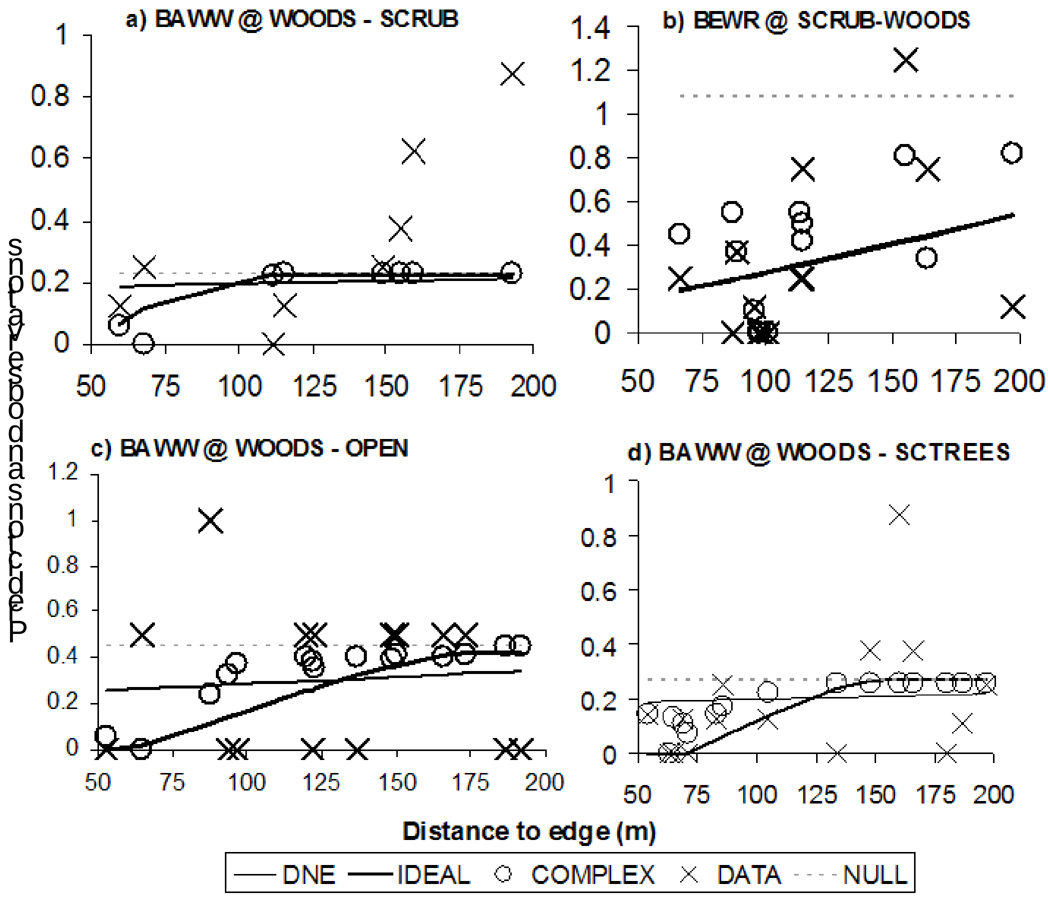


Figure 19. The predictions of four competing models (DNE, IDEAL, COMPLEX, and NULL) are compared to field observations (X's) for two additional species on Ft. Hood: BAWWs at Woods-Scrub edges (a) BEWRs at Scrub-Wood edges (b), BAWWs at Woods-Open edges (c) and Woods-Sctrees (d).

ideal version (as shown in Fig. 17 and also in Fig. 19b), but in other cases predictions are similar to the IDEAL model (i.e., Fig. 18a and Fig. 19a,c,d).

To compare observations to the predictions of the four models, we calculated the mean prediction error (PE = |obs-pred|; after Brand et al. 2006). Bootstrap methods are recommended to determine whether mean PEs of the four models differ significantly from each other (Brand et al. 2006), but we have not yet implemented that approach. The Malcolm model has the lowest mean PE when comparing the four models, although not always for the COMPLEX version of the model (Table 3). The NULL model almost always has the highest PE (Table 3) and therefore could be considered the worst model, suggesting that taking edges into account in predictions is usually helpful for species where significant edge responses have been demonstrated. In general, models that incorporated edges in some fashion were clearly better for GCWA, BCVI and BEWR, but not for BAWW which had the weakest edge responses as originally measured (see Table 2). Interestingly, there seemed to be little agreement between the "best" model for developing the parameters (Table 2) and the "best" model for testing the parameters (Table 3).

Table 3. Mean Prediction Error (|obs-pred|) for four models.
Black bold indicates "best" model, red is "worst" model

		Mean Prediction Error			
GCWA		NULL	DNE	IDEAL	COMPLEX
	WOODS-OPEN	**0.533571**	0.479838	**0.447792**	0.4865604
	WOODS-SCRUB	**0.459643**	**0.342518**	0.374295	0.4342973
	WOODS-SCTREES	**0.599048**	0.499137	**0.44108**	0.4602306
BCVI					
	SCRUB-WOODS	**0.596154**	0.507692	**0.440588**	0.5182701
BAWW					
	WOODS-OPEN	0.27	0.27872	**0.267058**	**0.2877897**
	WOODS-SCRUB	**0.208125**	0.21095	0.217064	**0.2311521**
	WOODS-SCTREES	**0.195069**	0.162789	0.136651	**0.129983**
BEWR					
	SCRUB-WOODS	**0.788846**	0.270092	0.26793	**0.2334907**

We examined two possible factors that may have influenced the magnitude of prediction error. The first was distance to edge, with the expectation that, if edges were important factors driving ecological patterns, then the closer the point was to the nearest edge, the better the predictions would be (i.e., the lower the prediction error) for models that consider edges (DNE, IDEAL, COMPLEX) but not the NULL model. This pattern was strongly found for BEWRs (Fig. 20a), but only weakly for GCWAs (results not shown). Patterns for BCVIs and BAWWs were more variable, although generally prediction error was somewhat lower near edges. Another factor we examined was how strongly predictions deviated from IDEAL when complex edge geometry was taken into account. These deviations are best illustrated in Fig. 17, and it might be expected that when edge responses are stronger based on edge geometry (so negative deviations from IDEAL) that prediction error would be lower. Again, a strong pattern in support of these predictions was only found for BEWRs (Fig. 20b), with a weak pattern again evident for GCWAs, and the opposite pattern found for BCVIs (results not shown). It is possible that an interaction between distance to edge and deviation from IDEAL is occurring, but we have not yet examined that possibility.

Our results suggest that predictions from Malcolm's model can differ strikingly from simpler measures, even when ideal geometry is assumed. Predictions are most strongly impacted when actual edge geometry is incorporated and these differences can be substantial (as in Fig. 17) or modest (as in Fig. 19a,c,d). However, incorporating edge geometry (the COMPLEX model) led to the best predictions in only 2 of 8 cases (Table 3). In half the cases, the IDEAL model performed best, with the DNE and NULL models each showing the best performance in one case each. This means that Malcolm's model, whether implemented assuming ideal geometry or incorporating complex geometry outperformed other models in 6 of 8 cases. This suggests that using Malcolm's approach may be valuable, but that accounting for actual edge geometry (the most difficult aspect of the model) may not be required, at least for some cases. However, since the design of the Ft. Hood survey network was not designed to test Malcolm's model (or any other edge model), local differences may have swamped important patterns, and

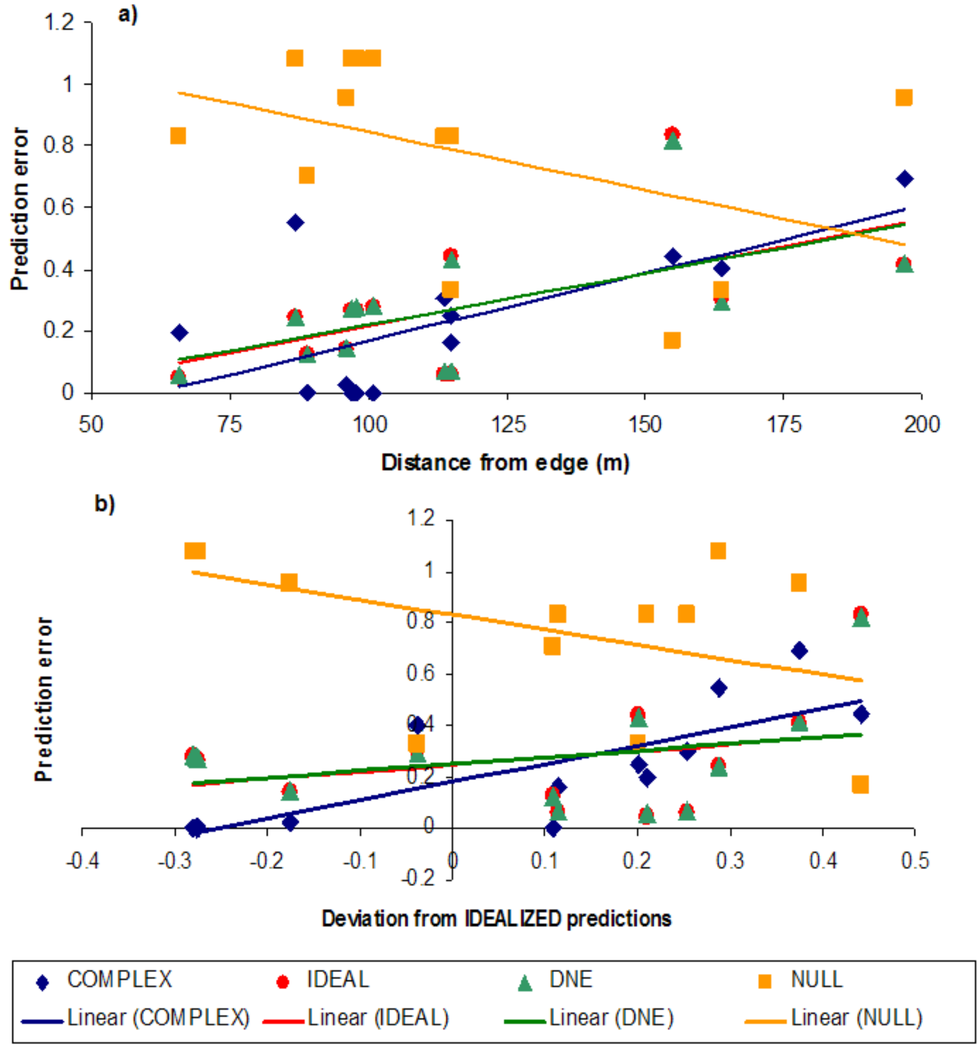


Figure 20. For the BEWR at SCRUB|WOOD edges, the relationship between prediction error and distance to closest edge (a) and predicted deviation of the COMPLEX model from an IDEALIZED realization (b).

tests designed specifically for this purpose may lead to stronger inferences about the importance of incorporating edge geometry into predictions of abundances across landscapes. Finally, predictions from the NULL model, which ignores edge dynamics, were the worst in 6 of 8 cases, stressing the importance of accounting for edge dynamics, even if only the simplest approaches are implemented.

5.3 Advances in Modeling when Data are Lacking

When no data are available to parameterize edge responses, information about habitat associations and resource use of local species can be used to generate categorical edge response predictions (positive, negative, and neutral) for any species of interest (Fig. 1c). Several applications of this model have shown that it does a good job of correctly predicting the direction of observed responses, but that it tends to overpredict responses (Ries et al. 2004). As an example, our predictions at Ft. Hood were largely correct when a response was observed (Table 2). This has important implications for applying the EAM on landscapes using hypothetical responses for an entire community based on our edge response model. It is likely that we can identify the most likely direction of edge responses that are occurring. However, we are also likely to predict responses where none occur. This has community-scale implications since, in general, only a portion of the community is likely to respond in any important way to shifting landscape structure per se. This was also demonstrated at Ft. Hood where only four of the six species predicted to show edge responses did, and then only at some of the predicted edges. Being able to identify species that are most likely to be sensitive to edges, and when they should be most sensitive, would constitute a major advance for making predictions on a community scale (Ries and Sisk, *in press*).

We have developed a framework for studying edge sensitivity and suggest that sensitivity, rather than direction of observed edge responses should be used as a more helpful characteristic for categorizing species in the future (Ries and Sisk, *in press*). To support this argument, we presented results from our work on butterflies on the San Pedro River suggesting that species more vulnerable to predation or with lighter-colored wings are potentially more sensitive to edges (Ries and Sisk, *in press*). Further, other projects that compared responses among multiple species have found that certain traits are associated with the probability of observing avian responses at forest-open edges, including ecological plasticity and nest placement (Brand 2004) or feeding guild (Kennedy et al., *in press*). All of this work suggests that it is possible to pinpoint certain members of the community as being the most likely to respond to edges, however, since this is a new concept, there has been as yet little work compiling results from the literature to pinpoint characteristics associated with edge sensitivity – or to establish new field studies to specifically test characteristics hypothesized to be associated with sensitivity. Nevertheless, we consider this to be an exciting new direction for future edge research. A new literature review, especially of papers published in the past six years to capture results not included in the extensive reviews done to date (Brand 2004, Ries and Sisk 2004, Ries et al. 2004) would be a useful start to this new avenue of research.

This issue pertains to our current project because, other than for RCWs, we have no data on how different members of the bird community at Ft. Benning respond to the different habitat mosaics captured in current and possible future landscape structures. Drawing on our existing edge response model, we could use information about species' habitat associations and resource distributions to make predictions about likely edge responses. Based on past tests of the model, however, we would likely see only a portion of the community responding at all, but which members are most likely to be sensitive? The past research (Brand 2004, Kennedy et al., *in press*) suggests insectivores and ground nesters might be most sensitive – but that research was entirely conducted at forest-open edges, so may not apply since Ft. Benning is made up of a mosaic of different forest types. Because it seemed preliminary to apply this framework to identify which members of Ft. Benning's bird community would be most appropriate for modeling, we did not model the responses of particular species. Instead, we grouped species into categories based on similar habitat associations, then developed parameters for the members of each group that are sensitive to edges. We called these "characteristic pseudo-species". In the future, it may be possible to identify species that are most or least likely to respond to landscape context and structure. In the meantime, we feel it is informative to model the most likely responses of sensitive members of each habitat group.

5.4 Results from the Ft. Benning Demonstration Project

Step 1: Identify Management Needs

We met several times with the resource managers on Ft. Benning to clarify approaches for applying the EAM toolkit in a manner relevant to base management challenges. Early meetings (prior to the start of BRAC planning) suggested that little landscape-level planning was occurring on the base, with the exception of a general goal to restore as much old-growth, long-leaf pine habitat as possible (Pete Swiderick, *personnel communication*). After discussions with several members of the Ft. Benning management team, we focused on two issues: determining the impact of tank trail activity and exploring how restoration for RCWs might impact the larger ecological community. Later, as Ft. Benning became the focus for relocating large numbers of troops as part of BRAC activities, we used the BRAC scenarios developed by the University of Washington team to model potential ecological impacts. Although none of our scenarios represent the actual choices facing managers, they are reasonable representations of the types of issues that could be under consideration.

Although our work with Ft. Benning did not end up incorporating actual management alternatives being considered by landscape managers, the recent planning for adding ranges under BRAC realignment shows how landscape-level planning does occur at military bases. While we unfortunately were not made part of that initial planning process, we think that our approach could have been informative and we hope that we can become involved earlier in similar processes in the future. We were invited in spring 2009 to use the EAM to explore different scenarios being run by Ft. Benning (post-BRAC planning) that had to do with trying to improve RCW habitat, especially in the face of substantive forest loss (Don Imm, *personal communication*). However, these scenarios largely focused on forest health and the inclusion of parcels for the Army Compatible Use Buffer Program (ACUB) to mitigate on-base losses. It would be difficult for us to include forest health in our modeling without substantial information on the impacts of forest health on habitat quality, but the ACUB units were relevant to the types of predictions made by the EAM. Unfortunately, only ACUB habitat was mapped and not the surrounding parcels. Thus, implementation of the EAM would have necessitated a large mapping effort on our part (similar to what we had to do on Ft. Hood to develop basic habitat maps, see section 3.3) and this was not feasible, due to both time and budget constraints. As Ft. Benning is contemplating the sizeable modifications being proposed under current BRAC planning (Fig. 2b), interest has grown in the potential ecological impacts of these actions. Ft. Benning has recently established a network of bird point counts to measure the ecological impacts of the BRAC modifications, and those data could be used in future modeling efforts using the EAM at Ft. Benning.

Step 2: Developing Edge Response Parameters

As noted above, there are very few data on bird distributions (other than RCWs) at Ft. Benning and none that could be used to develop edge response parameters for multiple species. As described in section 5.3, only a portion of the avian community may be sensitive to edges and fragmentation. Therefore, we decided to model responses for characteristic "pseudo-species" that represented a set of species that had similar habitat associations. Results for each pseudo-species are indicative of how any edge-sensitive species in each habitat group is likely to respond. While this is a simplifying generalization, it represents an appropriate level of abstraction, given the limited data available and the similarity of species within particular ecological guilds common to the installation. We began by analyzing the community structure of birds on Ft. Benning to determine how species clustered in terms of their habitat associations. After gathering information on all 70 species recorded in LCTA surveys (not including raptors, waders or waterfowl), we placed each species into a category that captured both its habitat associations and known or predicted edge responses (based on whether they were known interior species or known cross-boundary foragers). In general, interior species avoid edges and cross-boundary foragers are likely to be more common along edges where they preferentially forage (Ries and Sisk 2004). We used a combination of Birds of North America accounts and LCTA data to classify species into several categories. A complete list of habitat categories and associated Ft. Benning species is in Table. 4.

Table 4. Bird species[1] of Ft. Benning and their habitat associations

Species	Habitat Group	Edge Info[2]	Species	Habitat Group	Edge Info[2]
Red-cockaded woodpecker	Mature Pine	Prefers	Red-headed woodpecker	Hardwood	CBF
Brown-headed nuthatch	Mature Pine	NoInfo	Northern parula	Hardwood	CBF
Bachman's sparrow	Mature Pine	NoInfo	Acadian flycatcher	Hardwood	Interior
Pine warbler	Pine or mixed pine	NoInfo	Kentucky warbler	Hardwood	Interior
Chipping sparrow	Pine or mixed pine	NoInfo	Red-eyed vireo	Hardwood	Interior
Yellow-throated warbler	Pine or mixed pine	NoInfo	Balck-and-white warbler	Hardwood	Interior
Eastern wood-pewee	Forest generalist	NoInfo	Prothonotary warbler	Hardwood	Interior
Blue jay	Forest generalist	CBF	Louisiana waterthrush	Hardwood	Interior
Northern flicker	Forest generalist	CBF	Hooded warbler	Hardwood/Mix	Interior
American robin	Forest generalist	CBF	Wood thrush	Hardwood/Mix	CBF
Ruby-throated hummingbird	Forest generalist	CBF	White-breasted nuthatch	Hardwood/Mix	CBF
Chuck-will's widow	Forest generalist	CBF	Yellow-throated vireo	Hardwood/Mix	CBF
Summer tanager	Forest generalist	CBF	Tufted titmouse	Hardwood/Mix	NoInfo
Blue-gray gnatchatcher	Forest generalist	CBF	Downy woodpecker	Hardwood/Mix	NoInfo
Great-crested flycatcher	Forest generalist	CBF	White-eyed vireo	Shrub generalist	NoInfo
Carolina chickadee	Forest generalist	CBF	Yellow-breasted chat	Shrub generalist	NoInfo
Pileated woodpecker	Forest generalist	NoInfo	American goldfinch	Shrub generalist	NoInfo
Hairy woodpecker	Forest generalist	NoInfo	Common yellowthroat	Shrub generalist	NoInfo
Red-bellied woodpecker	Forest generalist	NoInfo	Rock dove	Urban/Suburban	NoInfo
Fish crow	Forest generalist	NoInfo	Mourning dove	Urban/Suburban	NoInfo
Northern cardinal	Shrub (in forest)	NoInfo	European starling	Urban/Suburban	NoInfo
Yellow-billed cuckoo	Shrub (in forest)	NoInfo	Chimney swift	Urban/Suburban	NoInfo
American redstart	Shrub (in forest)	NoInfo	House finch	Urban/Suburban	NoInfo
Carolina wren	Shrub (in forest)	NoInfo	Barn swallow	Urban/Suburban	NoInfo
Borwn-headed cowbird	Forest edge	Prefers	Purple martin	Urban/Suburban	NoInfo
Eastern kingbird	Forest edge	Prefers	Common grackle	Urban/Suburban	NoInfo
American crow	Forest edge	Prefers	Loggerhead shrike	Open	NoInfo
Prairie warbler	Forest edge	Prefers	Common nighthawk	Open	NoInfo
Gray catbird	Forest edge	Prefers	Eastern meadowlark	Open	NoInfo
Blue grosbeak	Forest edge	Prefers	Northern rough-winged swallow	Open	NoInfo
Orchard oriole	Forest edge	Prefers	Red-winged blackbird	Open	NoInfo
Indigo bunting	Forest edge	Prefers	Ground dove	Open	NoInfo
Eastern towhee	Forest edge	Prefers			
Brown thrasher	Forest edge	Prefers			
Field sparrow	Forest edge	Prefers			
Northern bobwhite	Forest edge	Prefers			
Eastern bluebird	Forest edge	Prefers			
Northern mockingbird	Forest edge	Prefers			

[1]Excludes raptors, waders, and ducks

[2]Prefers=known preference for edges; Interior=associated with interior habitat; CBF=Cross-boundary forager

We then focused on a subset of categories to develop edge response parameters that were intended to capture the most likely responses from species in that category. Categories were chosen because they represented either dominant portions of the bird community or species restricted to key habitat types subject to land management activities that are common on Ft. Benning (Table 4). Modeled and not-modeled groups are listed below, along with reasons for inclusion or exclusion.

- Groups that were modeled as characteristic pseudo-species:
  - Mature pine species (the "flagship" habitat type on Ft. Benning)
  - Pine generalist
  - Hardwood interior species (has the most "sensitive" species that are not listed)
  - Hardwood Cross-Boundary Forager (CBF)
  - Forest generalist (there are no "interior" species, so this group will be represented by a CBF)
  - Shrub specialist (in forest)
  - Forest/Open edge specialist (BRAC and restoration scenarios only)

  The following groups were not modeled:
  - HW and MIX species (these were expected to show similar responses to the Hardwood pseudo-species, except with higher densities in MIX)
  - Urban specialist (of little conservation interest – habitat rare and not monitored on Ft. Benning)
  - Shrub Generalist (open habitat is rare on Ft. Benning, most shrubs occur in forests)
  - Open habitat (open habitat is rare on Ft. Benning)

In order to develop edge response parameters, we chose one species from each model group as a guide, and then developed parameters using the following guidelines:

- Identify preferred habitat types and describe where the guide "species" shows its highest, lowest and intermediate density
  - Edge functions are based on our model (Ries and Sisk 2004; exceptions noted when appropriate). Interior species are predicted to avoid edges (with spillover into adjacent habitats), CBFs are predicted to prefer edges. When there is no habitat preference data for CBFs, no edge response is predicted between habitats with the same predicted density. Edge responses are assumed to be equally bilateral (the midpoint of responses within the edge zone occurs exactly at the edge) unless otherwise indicated.
  - Develop response parameters within the following constraints:
    - Highest interior density is always 1 ind/ha
    - Intermediate density is always 0.5 ind/ha
    - Density in non-habitat is always 0 ind/ha
    - Mid-point used for transitional responses, 50% increase for cross-boundary foragers (higher of two if at edge of adjacent habitat with different interior densities)
    - No response to MILITARY or WATER cover classes

        - Dmax is always 100m, and Dmin is always 0m
    - While these constraints clearly generalize actual responses, they are simplifications that reflect general patterns in the avian community and facilitate the comparison of base management scenarios which is the primary objective of this application of the EAM. More realistic response models could be developed using data currently being collected on Ft. Benning if it is decided this should be a focus of future research.

Based on these rules, we developed parameters for seven characteristic pseudo-species:

PNIN:	Mature pine specialist (modeled after the brown-headed nuthatch)
PNED:	Pine generalist (modeled after the pine warbler)
HWIN:	Hardwood interior species (modeled after red-eyed vireo/Acadian flycatcher)
HWED:	Hardwood cross-boundary forager (modeled after northern parula)
FORG:	Forest generalist (modeled after the summer tanager)
SHRB:	Forest/shrub specialist (modeled after the Carolina wren)
EDSP:	Specialist at forest/open edges (modeled after the eastern bluebird)

We also developed a set of parameters that will allow us to perform a sensitivity analysis on how the strength of the edge effect may impact observed patterns. We focused on one of our characteristic pseudo-species and varied the magnitude and strength of the edge responses to explore how the strength of local edge response influences predicted responses at the landscape scale. We used the Hardwood interior species (HWIN) as a starting point. As is true for the other six characteristic species, HWIN reaches its edge density at 0m (Dmin = 0) and its interior density at 100m (Dmax = 100). Where habitats with differing interior densities meet, edge responses are assumed to be perfectly bilateral (by which we mean the mid-value falls exactly at the edge and Dmax mirrors the same distance on each side of the edge).

To explore the role of varying the strength of edge response, depth and magnitude were varied in a systematic manner:

- Three ways of varying response:
    - Skewness: Bilateral (50% of gradient is in the focal habitat) or skewed (100% of gradient is in the focal habitat)
    - Dmax: 100m and 200m
    - Dmin: 0, 25m and 50m (with Dmax at 100m)
- A partial factorial combination of these factors results in six ecologically plausible combinations of parameters (one of which is part of the above set, so five new edge variants result):
    - Bilateral edge response (100 and 200m) – mid-point at 0m
        - » T200 (T100 represented by HWIN)
    - Skewed edge response (100m and 200m) – reaches core density of adjacent habitat at 0m
        - » A100 and A200
    - Extreme edge response (reaches edge density at 25 or 50m – Dmax set at 100m)

» XT25 and XT50

Edge response parameters for seven characteristic pseudo-species and five variants for HWIN were used in all three sets of scenarios developed for this demonstration project.

Steps 3-5: Scenario Modeling on Ft. Benning with the EAM

We developed and ran models on three sets of scenarios at Ft. Benning: road, BRAC and restoration scenarios. We present the results for the next three steps (developing scenarios, running the model, and analyzing results) grouped by scenario type.

Road Scenarios: Exploring Model Sensitivity to Differences in Road Density and Configuration

Tank maneuver exercises cause breaks in the canopy (Fig. 21a) that can impact both abiotic and biotic processes. Roads and trails on Ft. Benning show a great deal of variability in density across the landscape (Fig. 21b) and our goal was to determine how road density may impact the ecological community through edge responses and if there was any way to consider placing roads to ameliorate those effects. We modeled impacts on sensitive members of the bird community by assuming that species would respond to canopy breaks the same way they would to edges with open habitat. Our road scenarios are focused on only a portion of Ft. Benning (see red outline in Fig. 2a) because of the intensive process of simulating different levels of activity and the limited availability of actual road management plans. To simulate different levels of tank maneuvers, we iteratively added and deleted roads from the current configuration (based on a map we received from Ft. Benning in 2002). We began with the configuration of roads and trails provided to us by Ft. Benning (Fig. 22, center panel) which included about 400 km of trails within the model area (Fig. 2a). We then began to iteratively add and delete trails in increments of 100km. We ended up with nine classes of trail density, from 0km to 800km in the model area (Fig. 22). Building on our previous proof-

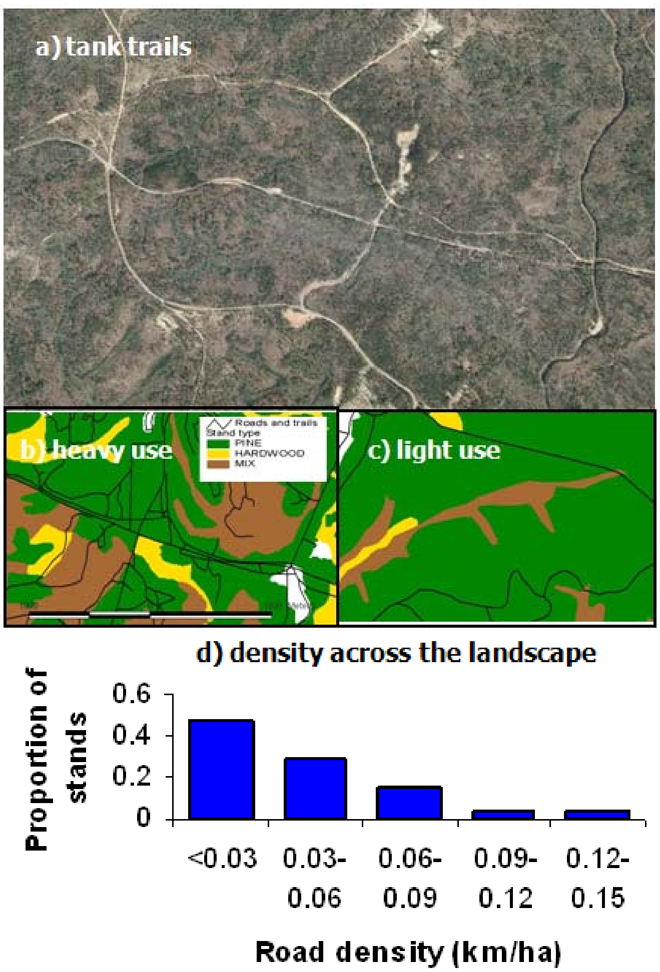


Figure 21. Tank trails on Ft. Benning (a) can be dense (b) or sparse (c). The distribution of road densities by stand across the landscape (d).

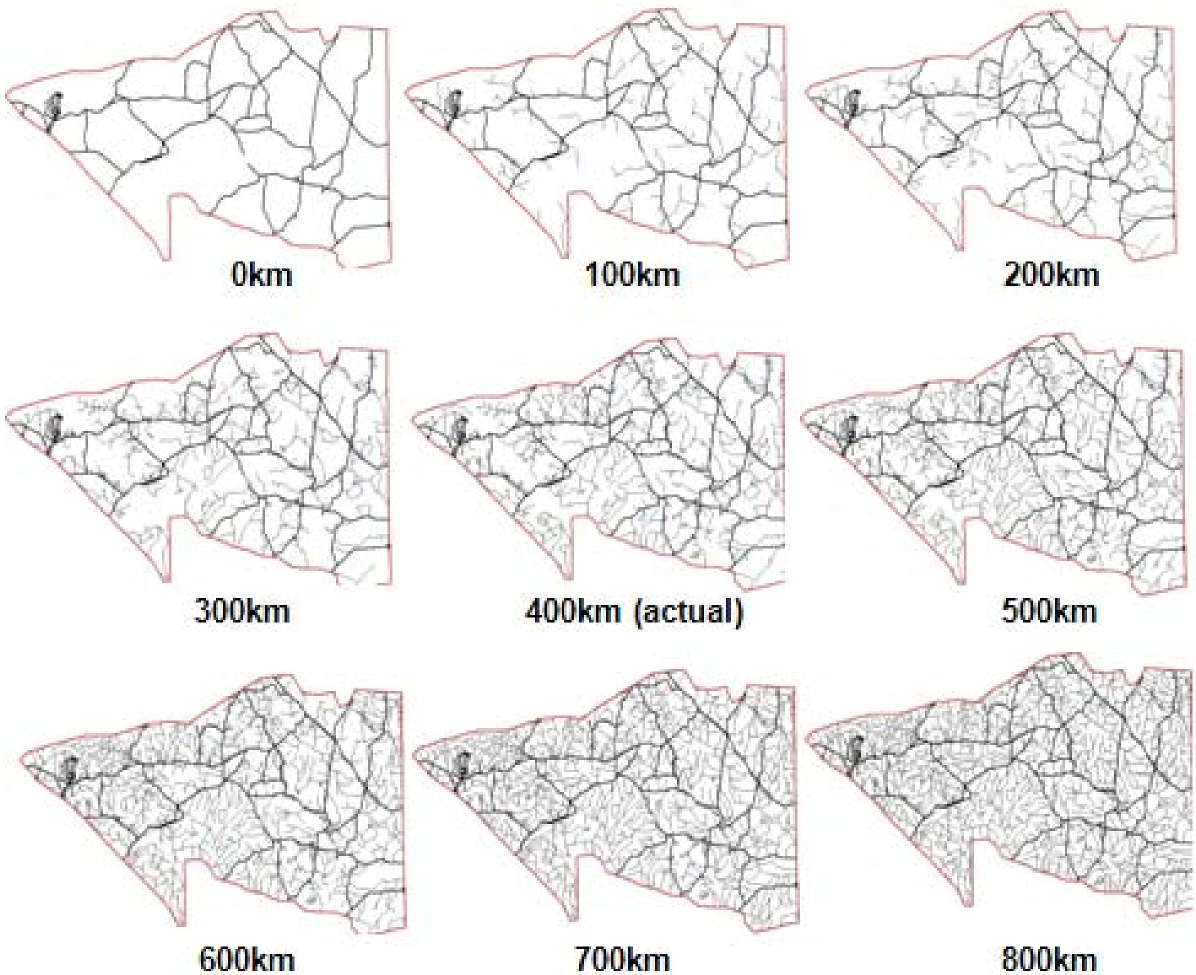


Figure 22. Road scenario maps for a portion of the Ft. Benning base targeted for modeling (see Fig. 3.3.1a). Trails were iteratively added and taken away from the actual road configuration (see middle cell) in increments of 100km, with 10 replicates created for each density class (except 0 and 400km) for a total of 72 scenario maps.

of-concept effort, we added statistical rigor to this simulation exercise by developing 10 replicate maps for each increment in trail density, where the configuration of deleted and added trails was varied haphazardly (except the 0 and 400km maps). This resulted in the creation of 72 trail maps (see Fig. 22 for examples). Each of these 72 trails maps was then processed in order to be used within the EAM. The trails were buffered, then unioned with the forest stand map (Fig. 23). To facilitate this process, we developed an ArcGIS custom toolbox to process these maps because many steps were required in order to make sure that key attributes were retained in the final maps. This toolbox can be used as a blueprint for others who plan to implement the same type of replicated scenarios, and is described on the EERC web site.

For tractability, we restrict our results for this report to four of the six pseudo-species (HWIN, HWED, PNIN, PNED) because these are the most habitat sensitive. Predicted population levels, integrated over the entire modeled landscape, show how incorporating edge responses results in very different predictions than those based on changes in habitat area alone

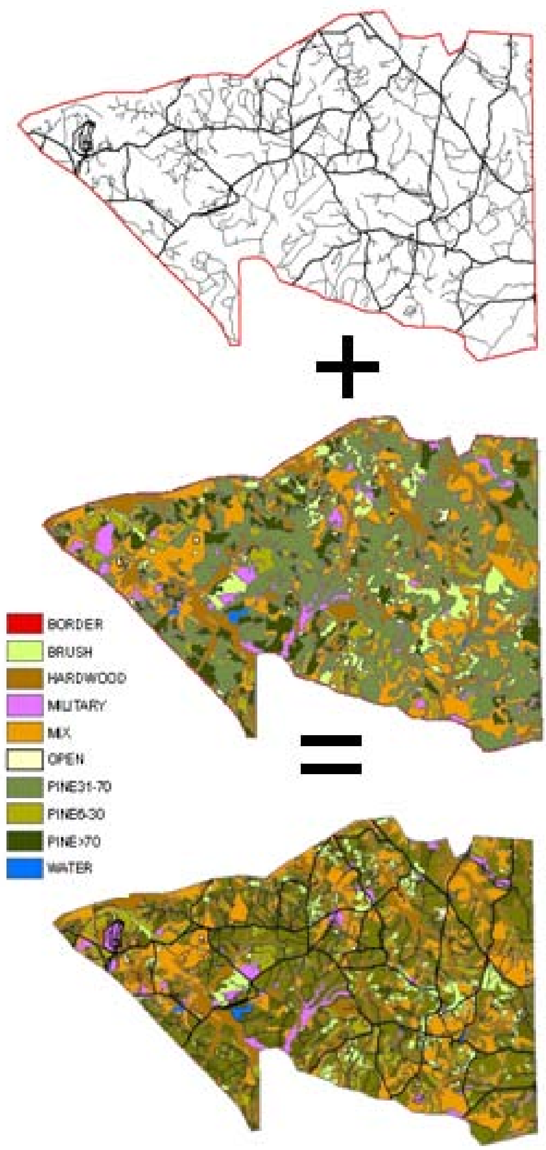


Fig. 23. Map processing for road scenarios involves intersecting with habitat maps, so all edges are considered in EAM modeling.

(Fig. 24). In these scenarios, habitat loss is minor, as reflected by the barely perceptible changes in predicted population levels under the null model, which ignores edge effects (red circles in Fig. 24). On the other hand, the EAM predicts substantial population changes for edge-sensitive members of some groups, particularly hardwood edge specialists, which are predicted to show a sharp decline; and old-growth pine specialists, which are predicted to increase. This seemingly counter-intuitive result is due to the way that trails are assumed to open the canopy, which can have positive effects on species adapted to the more open canopy structure of old-growth forests. Interestingly, there is little difference between the 10 replicates for any of these four “pseudo-species” (Fig. 24), although the hardwood edge pseudo-species shows more variable responses to the replicate scenarios (note the increased scatter in blue points in Fig. 24d). This suggests that, despite the fact that each replicate road map has a different configuration, those differences tends to cancel each other with respect to population size when integrated over an entire landscape. Finally, the substantial shift between predictions from the EAM compared to the NULL model suggests that predictions that ignore edge and context can lead to substantial over- or under-prediction of overall population size, assuming that edge responses are consistent and that edge effects would otherwise be ignored when developing habitat-specific density estimates (Fig. 24).

When examining patch-level results, differences become more pronounced. We present our results as mean density predicted for each individual patch on the landscape; each point in the graph represents a unique patch and configuration. Individual patches are represented for each unique configuration resulting from the haphazardly assembled road networks, based on realistic road density classes, as captured by the 72 maps. One of the most important results is that densities predicted by the EAM vary widely among patches (Fig. 25) suggesting that densities are strongly influenced by the surrounding landscape. Note that the NULL model predicts equal density across any gradient and is always pictured in graphs as a line at the corresponding density level (e.g., in Fig. 25). Because the EAM has no stochastic component to

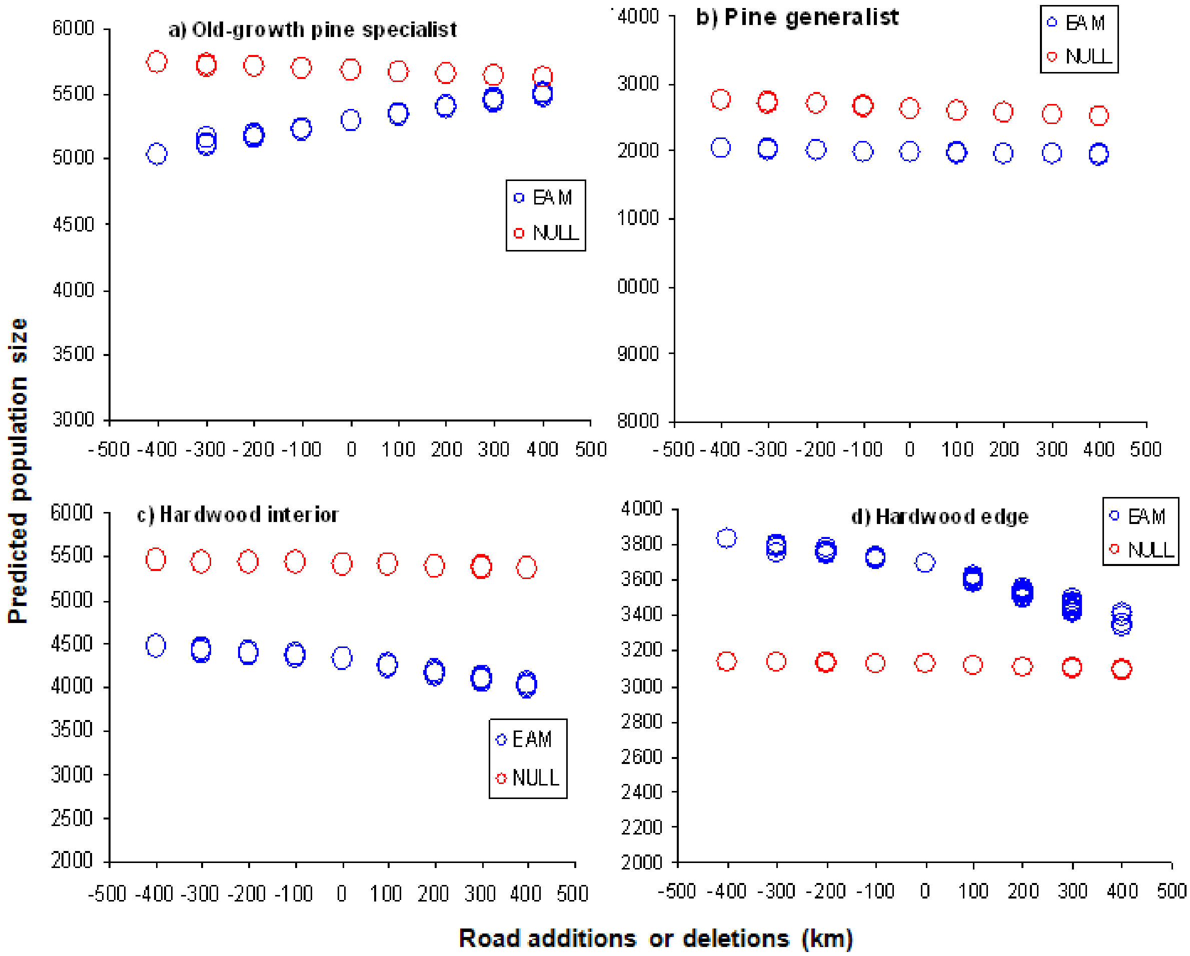


Figure. 24. Total predicted population sizes for four target "species" as roads are added and deleted throughout a model area on Ft. Benning. Predictions are shown for each scenario (10 replicates for each level of addition or deletion except 0 and -400) from the EAM and a NULL model that ignores edge and context.

add variability to predictions, the observed variability in EAM predictions derives solely from differences in landscape structure. Interestingly, the amount of habitat lost during road creation explains little of the variability in the data (Fig. 25). This result emerges because, despite the fact that roads were our topic of interest here, the EAM takes all edges into account. It is important to remember that the road network is layered over a habitat map that captures not only the habitat type, but the configuration and context of each patch as well (Fig. 23).

In order to explore potential underlying mechanisms, we use the patch metrics that are now generated by the EAM to determine how well other landscape factors explain the observed variability in predicted patch density. We explored several variables: patch size, mean distance to edge, total number of edge types, and the proportion of each patch that is surrounded by habitat that generates either a positive or negative edge response. Note that the first two candidate factors (patch size and mean distance to edge) are common metrics used to capture landscape structure and are usually correlated with the amount of edge (but they do not capture any information about the type of edge). The total number of edge types also doesn't capture edge quality, but constitutes an advance over typical edge metrics because it captures

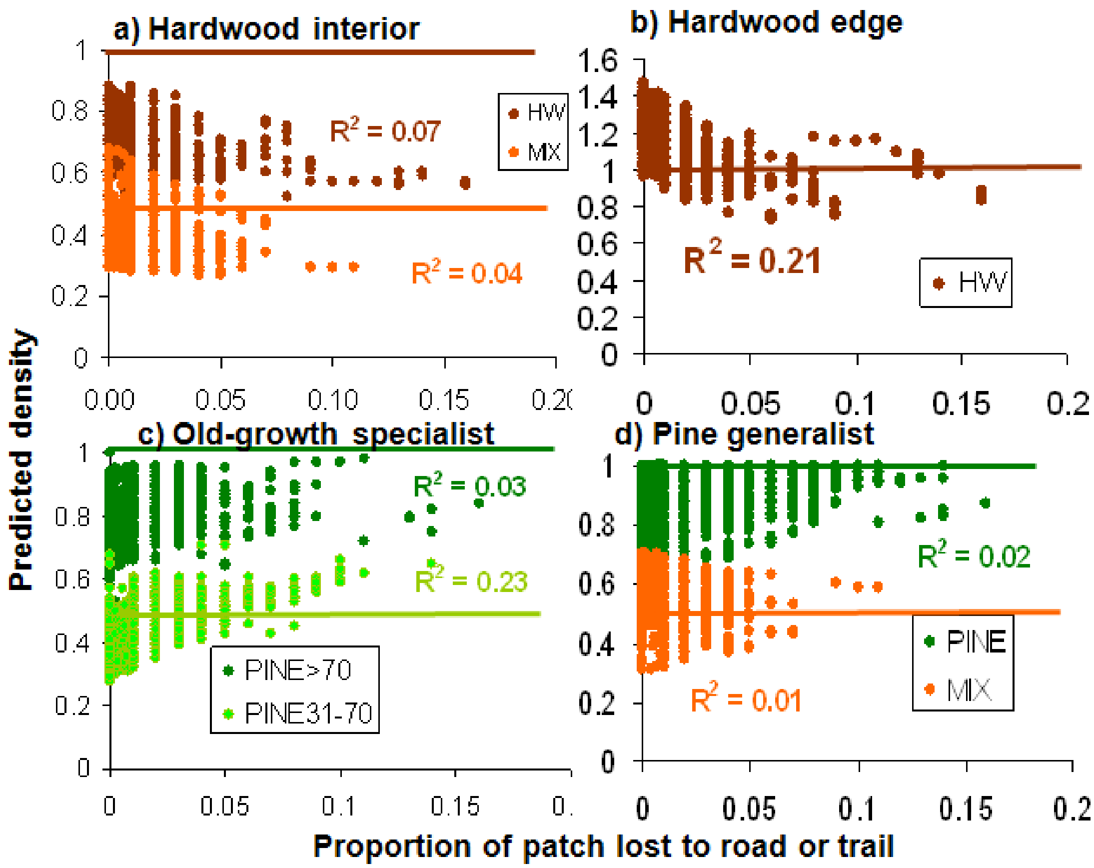


Figure 25. Patch-specific predicted densities for all unique configurations among the multiple scenarios of road density on Ft. Benning (Fig. 5.4.3). NULL predictions are constant across all patches and are shown by the colored lines.

information about the complexity of the landscape that each patch is embedded in. Only the last two candidate metrics, the amount of surrounding habitat that has either a positive or negative edge influence, captures information about the quality of the edges influencing each pseudo-species. Since much of our edge work has shown that the type of edge is critical to understanding responses (Ries et al. 2004, Ries and Sisk 2008), we suspected that these two metrics would far out-perform the others. However, these metrics (including the number of edge types) are the hardest to obtain and we are unaware of any program other than the EAM that could produce them.

Results are shown in detail for one pseudo-species (hardwood interior) in Fig. 26 and summarized for all four in Table 5. As detailed in step 2 above, the hardwood interior pseudo-species shows negative responses to most edges within HARDWOOD, with some neutral responses. Responses within MIX are more variable, with negative responses at several edge types, but positive responses near hardwood edges. This difference between the types of responses (negative or neutral only in HARDWOOD, negative, neutral and positive in MIX) is evident in the explanatory power of the different candidate variables shown (Fig. 26). In hardwood habitat, where responses are almost entirely negative (with the exception of neutral responses to rare habitat types), there is a much stronger pattern captured by simple metrics like patch area and mean distance to edge (Fig. 26b,c) in HARDWOOD, when compared to MIX habitat. However, in MIX habitat, only a metric that incorporates information on the quality of

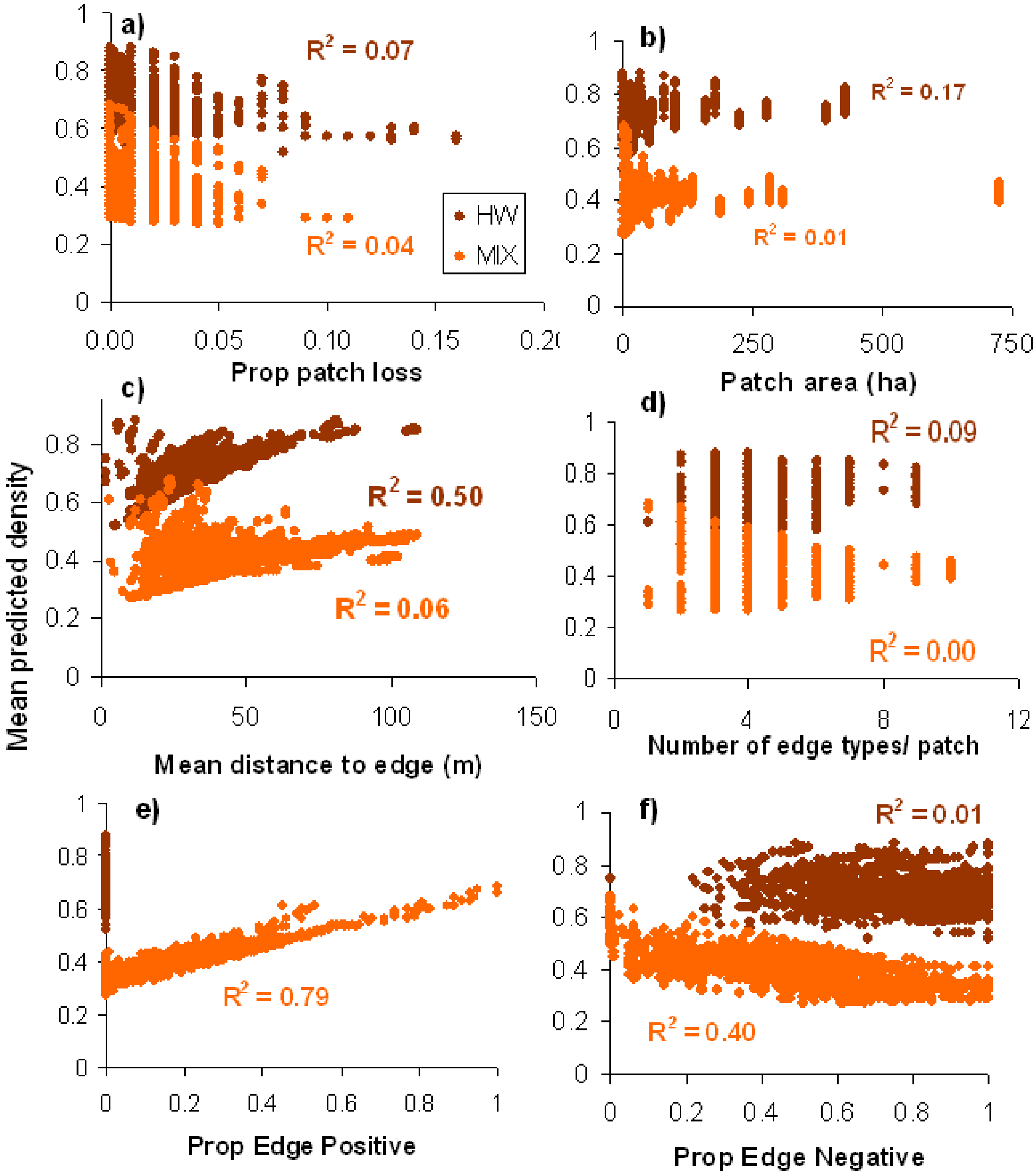


Figure 26. Alternate mechanisms to explain observed patterns in densities predicted by the EAM for a hardwood interior species in hardwood (brown) and mix (orange) forest stands.

the edges (Fig. 26e,f) captures edge responses adequately. For hardwood interior species in mixed habitat, only the metric describing portion of negative habitat (Fig. 26e) has any explanatory value.

When examining patterns across the community, it generally holds true that the densities of species with the most consistent responses are explained by the simpler patch metrics (size and shape), but that when responses are more variable, more nuanced edge metrics, which are

Table 5. Explanatory power of each variable for each species/focal habitat combination from Road, BRAC and RCW scenarios at Ft. Benning

Species	Focal habitat	Respose summary	Explanatory variable	Road	BRAC	RCW
Hardwood Interior	Hardwood	Avoids	Prop patch lost	0.07	0.14	
	Hardwood	most edges	Patch area	0.17	0.12	
	Hardwood		**Distance from**	**0.50**	**0.54**	
	Hardwood		No. edge types	0.09	0.27	
	Hardwood		Prop edge positive	na	na	
	Hardwood		Prop edge	0.01	0.28	
Hardwood Interior	Mix	Response	Prop patch lost	0.04		
	Mix	mixture	Patch area	0.01		
	Mix		Distance from	0.06		
	Mix		No. edge types	0		
	Mix		**Prop edge**	**0.79**		
	Mix		Prop edge	0.4		
Hardwood edge	Hardwood	Response	Prop patch lost	0.21		
	Hardwood	mixture	Patch area	0		
	Hardwood		Distance from	0.06		
	Hardwood		No. edge types	0		
	Hardwood		**Prop edge**	**0.86**		
	Hardwood		Prop edge	0.11		
Old-growth pine	Pine>70	Avoids	Prop patch lost	0.03	0.01	
	Pine>70	most edges	**Patch area**	**0.28**	0.13	0.08
	Pine>70		**Distance from**	0.24	**0.32**	**0.46**
	Pine>70		No. edge types	0.20	0.15	0.01
	Pine>70		Prop edge positive	na	na	na
	Pine>70		**Prop edge**	**0.64**	0.22	0.22
Old-growth pine	Pine31-70	Response	Prop patch lost	0.23		
	Pine31-70	mixture	Patch area	0.03		0
	Pine31-70		Distance from	0.01		0.02
	Pine31-70		No. edge types	0.1		0
	Pine31-70		Prop edge positive	0.13		**0.84**
	Pine31-70		**Prop edge**	**0.88**		**0.84**
Pine generalist	All pine	Avoids	Prop patch lost	0.02		
	All pine	most edges	Patch area	0.03		0.04
	All pine		Distance from	0.08		0.24
	All pine		No. edge types	0.1		0.03
	All pine		Prop edge positive	na		na
	All pine		**Prop edge**	**0.74**		**0.39**
Pine generalist	Mix	Response	Prop patch lost	0.01		
	Mix	mixture	Patch area	0.01		
	Mix		Distance from	0.02		
	Mix		No. edge types	0		
	Mix		**Prop edge**	**0.78**		
	Mix		**Prop edge**	**0.63**		
Edge specialist	Pine>70	Response	**Prop patch lost**		**0.45**	
	Pine>70	mixture	Patch area		0.05	0
	Pine>70		Distance from		0.16	0.03
	Pine>70		No. edge types		0.08	0.01
	Pine>70		**Prop edge**		**0.9**	**0.73**
	Pine>70		**Prop edge**		**0.34**	**0.27**

harder to compute, become necessary (Table 5). Many sensitive species may be the type of species that generally have more consistent edge responses (avoiding most habitat edges when in their preferred habitat) so simple metrics may suffice. When considering community responses however, simple metrics are likely to be insufficient.

We modeled five variants in edge response magnitude, compared to our typical edge response. The typical edge responses we developed (see step 2 above) sets Dmax at 100m and Dmin at 0m consistently across all species/edge combinations. Further, we assumed that transitional edge responses (like that shown in Fig. 1c) reach a mid-point in density at the edge, so the response is bilateral. Our five variants in edge response were generated by extending Dmax to 200m for the typical response (T200), or shifting the edge responses completely into the focal habitat, so that it is no longer bilateral. For this skewed response we kept Dmax at 100m (A100) and also extended it to 200m (A200). Finally, we extended the edge density into the focal habitat by setting Dmin from 0 to 25m (XT25) and 50m (XT50).

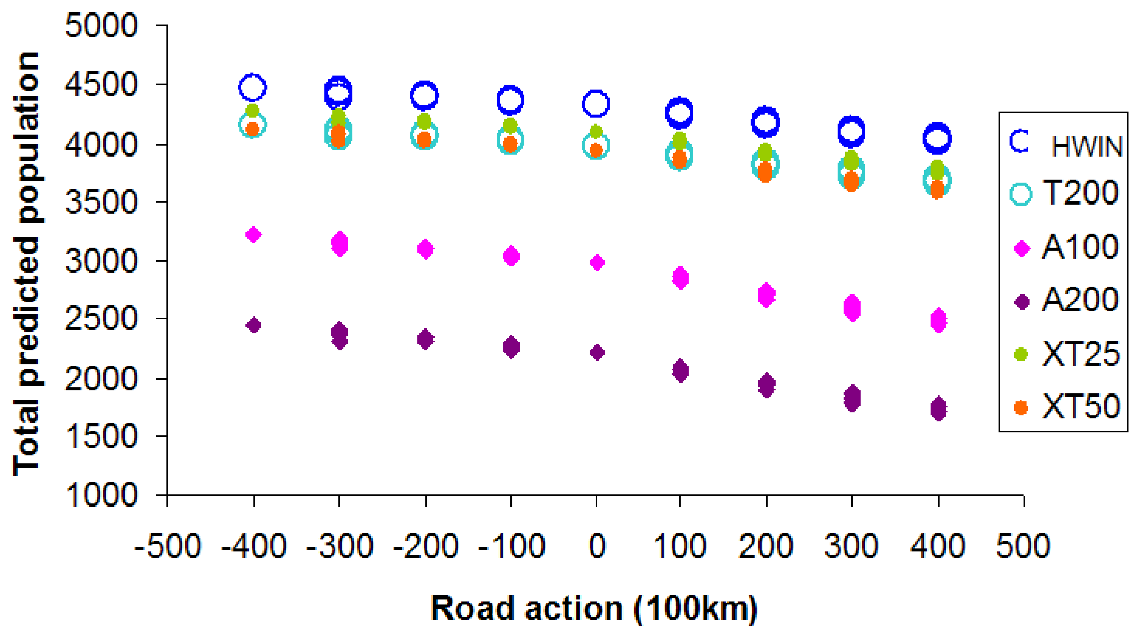


Fig. 27. EAM predictions for the hardwood interior species showing the same response from Fig. 5.4.5c (typical HWIN response with 100m Dmax) and five edge strength variants: typical response with 200m Dmax (T200), skewed response with 100m Dmax (A100) and 200m Dmax (A200), and when Dmin is set to 25m (XT25) and 50m (XT50).

Results are shown for the predicted total population size at the landscape scale (Fig. 27) and for density at the patch scale (Fig. 28). Interestingly, the strength of the modeled edge response doesn't change the predicted shape of the response pattern. Instead it causes a shift in predicted overall population size (Fig. 27) or density (Fig. 28). Surprisingly, changing Dmax or Dmin alone had only a very minor impact as opposed to shifting the skewness of the response (see responses for A100 and A200). In fact, when the response was bilateral (as is usually assumed), changing Dmax from 100 to 200m had a very minor impact compared to making the same change when the response was skewed (see A100 vs. A200 in Fig. 27).

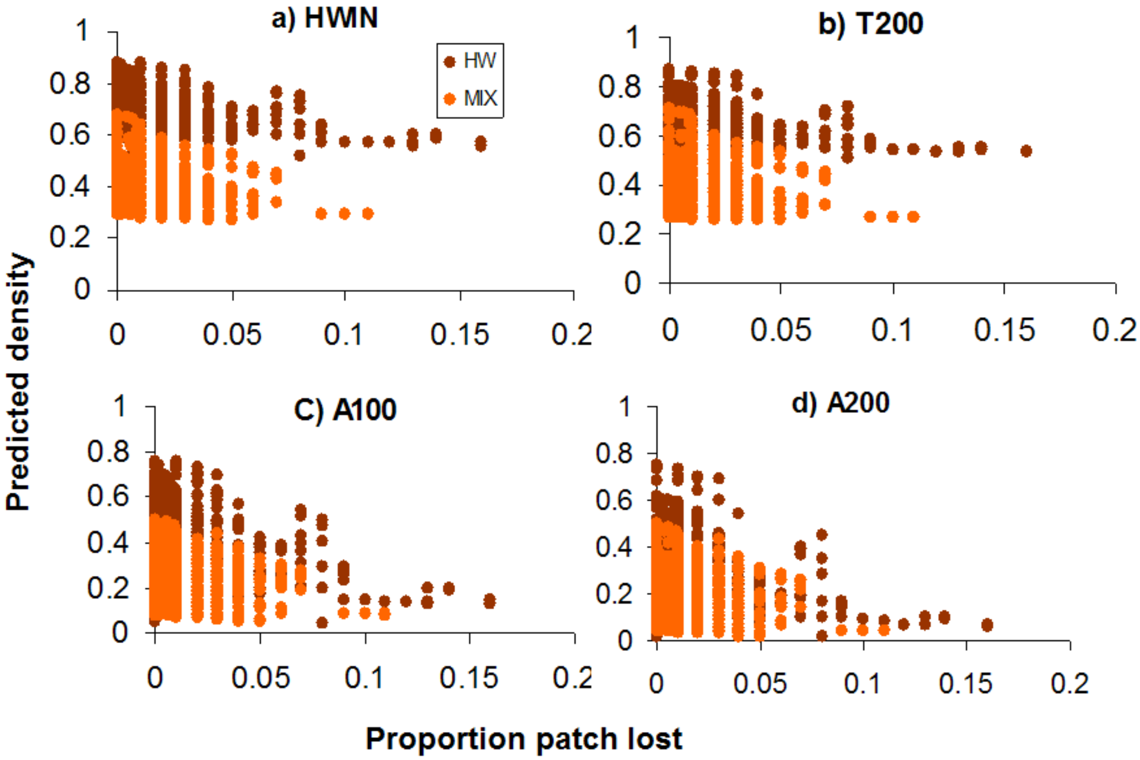


Figure 28. Patch-level responses for three of five edge variants (T200, A100, A200) compared to the typical HWIN response.

Another interesting result is the erosion of differences in the predicted quality between the best and marginal habitat for the hardwood species (Fig. 28). The null model would suggest a very distinct difference in predicted densities between the best and marginal habitat (see predicted lines in Fig. 25). When the typical edge response (T100) is taken into account, there is a slight overlap in the scatter of predicted densities of patches of the two focal types (Fig. 28a). This overlap becomes more pronounced when Dmax is increased to 200m (Fig. 28b). As the strength of the edge response increases through XT25 and XT50 (not shown) and A100 and A200, the degree of overlap increases (Fig. 28c,d). With the strongest edge response, the predicted difference between these two habitat types of very different quality has almost completely eroded (Fig. 28d).

StopNGo Mapping of Roads on Ft. Benning

One of the main results of our modeling on Ft. Benning is that different patches of the same type are predicted to have very different densities for each target species across a wide range of potential management activities (Fig. 25). This suggests that landscape context can either ameliorate or exacerbate the impacts of any particular activity – and could therefore be an important consideration when choosing sites for activities, such as military training or restoration. This realization has caused us to envision a new way that the EAM could be useful to managers, which we call "StopNGo mapping". The idea of StopNGo mapping is to color-code information into maps that may help determine the best sites for management action.

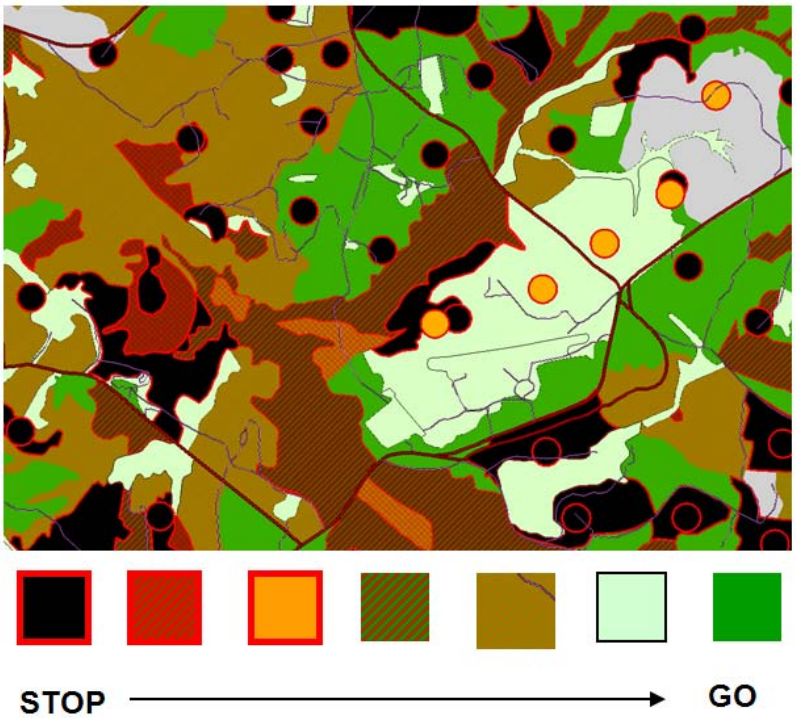


Figure 29. StopNGo map to plan roads on Ft. Benning. A series of rules was used to code polygons based on a combination of habitat type and ecological sensitivity (as measured by the EAM). Planners would be encouraged to plan for constructions in the green rather than red and black zones

Although the choice of colors can be arbitrary, we implemented a demonstration where we color-coded areas to be black or red where activity should be restricted and to green where activity should be encouraged (Fig. 29). Thus, the name StopNGo mapping comes from an implementation where actions are driven by "green means go" and "red means stop" rules that can be easily applied. This idea is not necessarily tied to the EAM, but the EAM can provide one source of information that could be encoded into a map. Other sources could include information about patch connectivity or information on the location of protected species. Further, the technique would not need to be used specifically to generate scenario maps, but could be used simply as a heuristic tool to help managers make more informed decisions. Based on our experiences at Forts Benning and Hood, this may offer a more approachable and practical implementation of the EAM or other landscape-level models.

Our concept of StopNGo mapping is a new one that is still under development. However, we have used the idea to develop an alternate series of road maps for Ft. Benning, and we performed identical analyses to those described above, so we are able to determine if the use of this technique is able to alter predicted outcomes for the better. To do this, we developed a set of four different rules that each represent different factors that a manager might need to consider when planning management actions. Note that, in this example, only two of the rules are related to landscape context, based on the rules coded into the EAM. Further, only one of the rules required the use of the EAM to actually color-code the rule into the map. We developed these rules with the primary goal of protecting the RCWs, then secondarily to benefit three other ecological groups: old-growth pine specialists, hardwood interior and hardwood edge species.

In order to implement our StopNGo mapping, we developed a color scheme to encode four rules (see Fig. 29). Rule 1: Don't place trails within 100m of a currently established or planned RCW nestbox. This rule was applied by buffering each existing and planned cluster, then color coded the buffered points as black (current) or orange (planned), both with a red border. Rule 2: Don't place trails in old growth pine (black polygons with red border). Rule 3: Avoid hardwood in general (red border), especially when the EAM indicates that impacts are ameliorated by context (red hatch), but less vigorously when the EAM suggests that impacts may not be ameliorated (green hatch). In this case, whether a patch is predicted to be ameliorated from impacts is based on predictions from the EAM (summed proportional difference between EAM and NULL predictions for hardwood interior and hardwood edge species calculated individually for each patch by the EAM). Mix habitat was also coded with red and green hatch to indicate which habitats were buffered or not. Rule 4: Target trails through younger pine stands because habitat quality is predicted to improve with a more open canopy structure (even when this is due to roads and trails). This rule was not patch specific, so didn't require output from the EAM, but instead is based on our hypothesized edge responses.

Using the map that resulted (a portion is shown in Fig. 29), we created 10 replicate maps using the same road addition/deletion levels as in the road scenario described above. When adding roads, they were allowed to go through "stop" areas, but they were avoided when possible while creating scenarios, but at the same time we attempted to make a realistic looking road network similar to the "haphazardly" created road networks created earlier (Fig. 22). When deleting roads, we preferentially deleted them from "stop" areas, but we had less flexibility in making these maps. We show results for the three species whose information we encoded in the StopNGo map to determine if using this technique leads to better predicted outcomes. There was only a little predicted improvement for the old-growth pine specialist (Fig. 30a). However, more substantial improvement was predicted for the hardwood interior species (Fig. 30b) and most dramatically for the hardwood edge species (Fig. 30c). For all species, the most noticeable impacts came in the scenarios where roads were added (positive values along the x-axis) rather than deleted. This suggests that this approach to guiding management choices may have more impact in planning new development rather than restoring or removing old development.

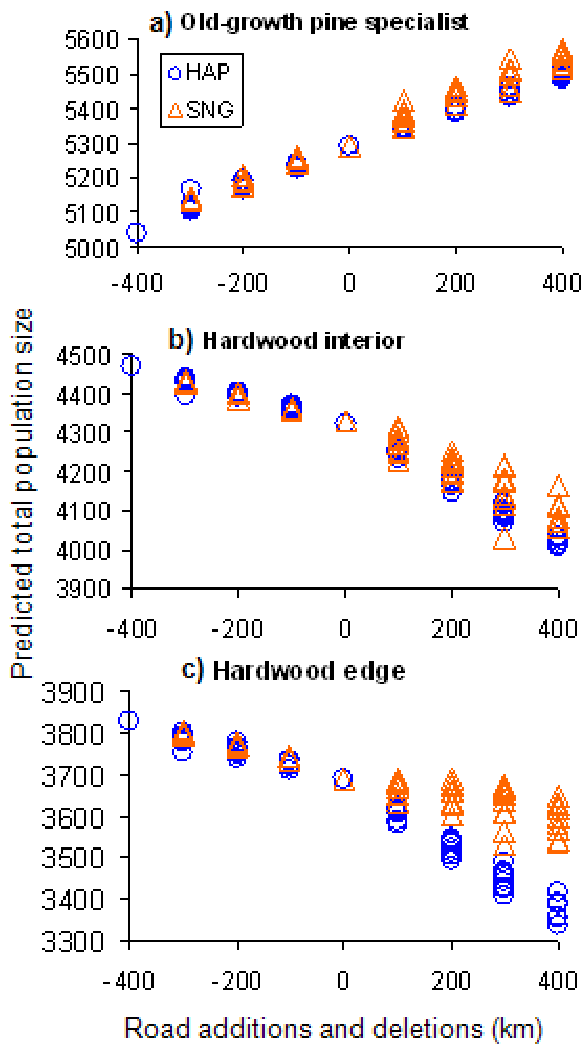


Figure 30. Total predicted populations for replicate scenarios representing different densities for roads drawn haphazardly (HAP) and roads drawn using StopNGo maps (SNG) for three "species".

We feel this approach has a lot of promise in bringing information about landscape-scale dynamics, using the EAM and/or other tools that focus on different factors (e.g., connectivity) to managers and planners in a practical manner. We believe that the benefit of this approach is that it conveys information without restricting choices. Finally, we implemented this demonstration using the same modeling framework as the road scenarios presented above. This allowed us to compare results and determine the efficacy of this approach. However, these tested multiple scenarios simply to demonstrate the extent to which they were able to impact predicted outcomes. There is no reason that a manager would have to develop alternate or multiple scenario maps. This approach could be used to simply guide or support decisions, without modeling multiple, alternative possible outcomes, which may not be tractable for time-stressed natural resources managers. That highlights another potential advantage of this approach. Managers would only need to parameterize and run the EAM one time, then use that output to develop a more informative "StopNGo" map that could be used as long as the habitat structure illustrated in that map remains current.

<u>BRAC Scenarios</u>

Road scenarios are useful for modeling edge effects because they remove very little habitat and they add a lot of edge. However, other types of development can create a much larger footprint, where large areas of habitat are lost or modified. The planned BRAC activity is an example where large habitat areas are removed so that significant portions or entire patches can be converted to other uses, essentially removing habitat from the landscape. We used BRAC activities to explore the impacts of such habitat conversion. In these cases, the added impact of edge effects may be relatively unimportant when compared to overall habitat loss. We received a series of scenarios simulating adding training ranges to Ft. Benning in nine 10-year increments to determine the potential impacts of future BRAC activities. As mentioned earlier, the amount of habitat altered in these scenarios is much less than the alterations currently planned (Fig. 2b), so we have come to view this set of scenarios as an opportunity to contrast with the results of the road scenarios where habitat loss at the patch and landscape level are minor but edge creation is high. These scenarios are also useful because range additions were modified to have high, medium, or low impacts on RCW habitat. This design gives us another chance to explore how ecological decisions driven by endangered species management may impact the larger ecological community. Each of the three impact levels is replicated four times. This results in a total of 108 scenarios (3 impact levels x 9 time steps x 4 replicates) that were run through the EAM (examples in Fig. 31).

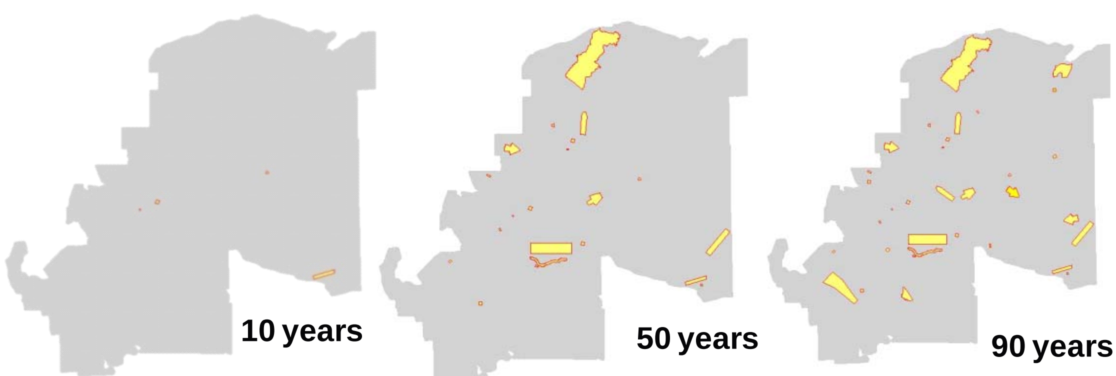


Figure 31. Examples of BRAC addition scenarios from three of nine time steps. These impact areas were assumed to convert forest to open areas. Each time step is replicated 12 times with 4 of each replicate having low, medium or high impacts on RCWs.

BRAC results were calculated for the same four species used in the road scenarios, but adding the edge specialist. We modeled the edge pseudo-species for the BRAC landscape because the proposed modifications add significant edge between open and forest habitat (as opposed to just the canopy breaks modeled in the road scenarios). Species such as bluebirds and others (see Table 4) can respond strongly to these types of modifications. Landscape-scale results are shown for three of the five species in Fig. 32. The same shift between the EAM and NULL models are expected and observed. Results for the pine and hardwood species (Fig. 32b,c) showed the expected differences between the EAM and the NULL models, but showed no difference in the population's trajectory in response to the planned activities (note parallel trajectories in Fig. 32b,c). This is in stark contrast to the results of the road modeling which showed divergent trajectories in response to road conditions for three of four species (Fig. 24). This suggests that habitat loss may be swamping the effects of edge in the BRAC scenarios; however we are continuing to explore this result. In stark contrast, an entirely new pattern emerged for the edge specialist where NULL and EAM predictions move in opposite directions (Fig. 32a). This may be because in pre-BRAC landscapes there is almost no open habitat (where the edge pseudo-species is predicted to respond strongly in a positive direction). At the same time, it avoids all forest edges which dominate completely in the pre-BRAC landscape. This result reflects a transformation of the landscape, and could be even more pronounced when the actual BRAC configuration is considered.

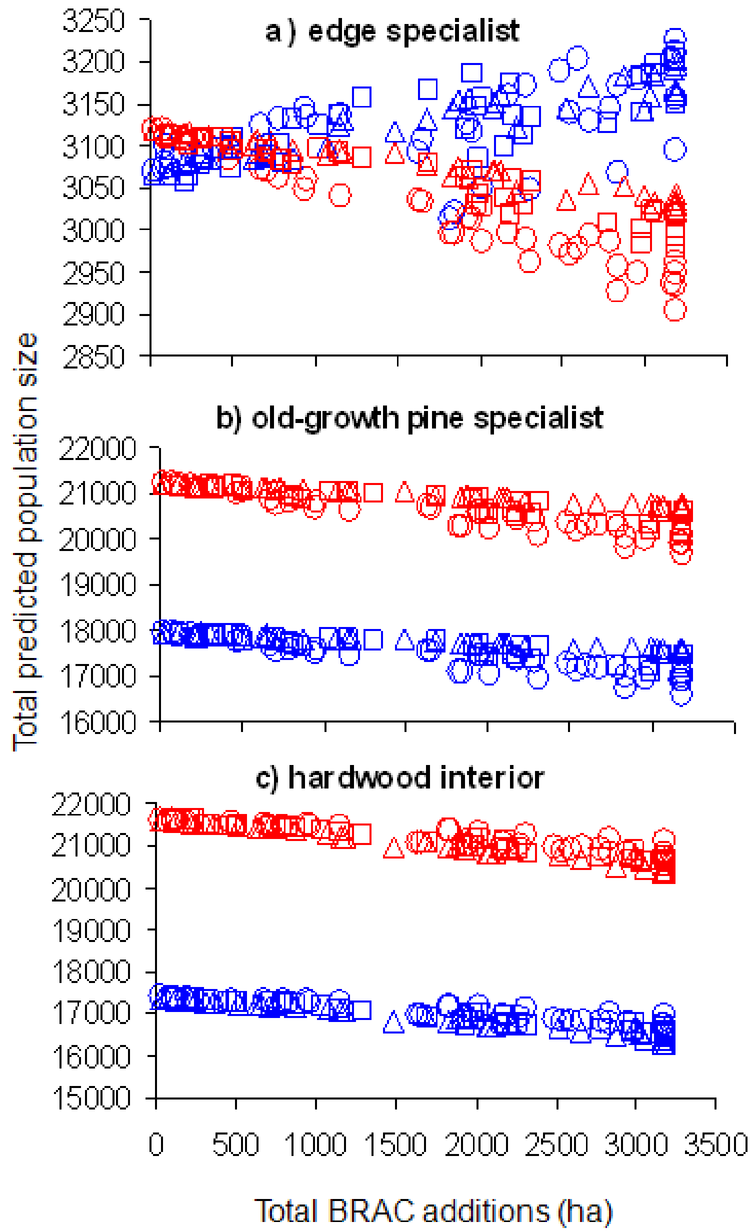


Figure 32. Total predicted population size after BRAC removals from the EAM (blue) and NULL (red) models. Removals occurred in configurations designed to have either low (square), medium (triangle) or high (circle) impacts on RCWs.

Another factor to note is that, while minor, the accounting for the level of RCW impact (shown by HIGH, MID, LOW) appears to have some impacts on results. The old-growth pine species shows higher predicted populations in the BRAC scenarios with the lowest planned impact on RCWs (Fig. 32b) with MID and HIGH impacts predicting progressively lower population levels as BRAC additions continue. This may not be surprising since the RCW has the same habitat requirements as the old-growth specialist (which was modeled after the brown nuthatch, not the RCW, see step 2 above). There seemed to be less impact on the other forest species (Fig. 32c shows hardwood specialist, but two other pseudo-species not shown), but clumping within the impact categories was still noted. Interestingly, the different impact levels seemed to have no effect on the predictions of the EAM for the edge specialist (blue symbols in Fig. 32a), but a pattern appears to emerge within NULL predictions (red symbols). It is unclear why this might emerge, but it could be that in the case of such an extreme edge specialist, configuration ends up mattering more that habitat placement.

When looking at underlying mechanisms, patterns similar to the road scenarios emerge (Table 5). Species that uniformly avoid edges have patterns best described by simple metrics, but species that have a mixture of responses require a more nuanced metric to capture the observed variability. In this case, that required knowledge of the actual habitat surrounding the patch of interest. Again, this has important implications because it suggests that only certain species (probably only habitat specialists) can have their edge responses reasonably captured by simple metrics such as patch size or shape. Results from the road and BRAC scenarios show important contrasts in how we might need to think about landscape-scale impacts on a community. When the area of habitat loss is great, edge responses may be swamped out for all but species whose habitat is primarily found at the edge.

Restoration Scenarios for the RCW

Ft. Benning lies within an ecological zone dominated by pine stands, historically long-leaf pine (*Pinus palustris*) based on soils and other data. An 1827 reconstruction (Olsen et al. 2007) of Ft. Benning suggests the landscape was once comprised largely of pine (75%), with mixed and deciduous forest much less common (12 and 8% respectively). After European settlement, extensive farming occurred and this activity greatly diminished the longleaf pine system until well after World War II and, by 1970, the extent of pine at Ft. Benning was down to approximately 25% (Olsen et al. 2007). Forestry practices, fire suppression, and development had further transformed the landscape on Ft. Benning, but much of the landscape has since returned to a more pine-dominated system, although stand age and composition likely differ substantially from pre-European states. One of the main long-term goals of the Ft. Benning managers is to return much of the landscape to its historical ecological state (Olsen et al. 2007). This would be beneficial to the RCW, the species that drives much of the conservation work because of its federally-protected status. The goal of returning the landscape to a more natural state is a long-term one, and somewhat at odds with currently proposed BRAC-related modifications.

If the goal is to return Ft. Benning to a more natural state, there are several topics that could be important to managers. We focus on three: 1) the final landscape configuration that could be targeted, 2) developing methods to move towards that final target, and 3) whether patches can be identified to maximize short-term benefits of restoration. The final landscape configuration will likely be based on the original land cover prior to European settlement, where pine-dominated stands made up 75% of the landscape (Olsen et al. 2007). Although the reconstruction gives a good general target for landscape-level planning, it can not be used to reconstruct patch-level structure or plan for patch-level decisions because the methods did not capture patch-level patterns. For instance, comparing the 1827 reconstruction to 1999 maps received from the base, the total number of patches was 131 and 61,519 respectively (Olsen et al. 2007) with mean patch areas for pine of ~3000 ha for the reconstruction, but only ~1 ha for the modern landscape (Olsen et al. 2007). While pre-European landscapes are likely to have fewer, larger patches, those differences could not explain the magnitude of the discrepancy between the two maps. Instead they are differences of method and scale, with smaller patches unlikely to be picked up by the data used to reconstruct the historic maps, which are based on "witness trees" marked every mile in grids during surveys that occurred in the 1800s (Olsen et al. 2007). For example, on the modern landscape, typical widths of most hardwood patches range from ~50 to ~500m (analysis not shown) from their narrowest to widest point and therefore would likely be missed by the survey techniques described above. Because these maps did not capture patch-scale distinctions, we did not use it to run the EAM which is a patch-scale model. Instead, we focused on processes that might occur over a long-term planning horizon that should move the base closer to the historical conditions described by Olsen and colleagues (2007). To do this, we developed a process where we both aged the forest and implemented restoration actions, in this case restoring 1500 ha of stands classified as pine-hardwood mix to pure pine stands every 10 years. We ran this process for 50 years and produced 5 replicate maps at each 10 year time step (Fig. 33).

The base map was acquired in 2002 from Ft. Benning showing the forest stand configuration. However, the map did not classify habitat in areas designated for military activity, including three large impact zones. Since these zones comprise much of the best RCW habitat on Ft. Benning (Pete Swiderick, *personal communication*), we wanted to include these zones in our modeling effort. We obtained an updated habitat map and decided to intersect the two maps since the updated map contained many non-overlapping polygons, which should not be allowed when running the EAM (see Appendix B). We used the newer map to replace the military zones from the older map with polygons from the new. This composite map was useful for our demonstration, but a next-generation map may be required for future planning.

To age the forest, we took the age of each stand given in the forest stand attribute table and added 10 years at each time step. Stands without ages were assigned values based on the mean stand age. Open and brush habitats were assumed to remain the same, although pine stands younger than six years were pooled with brush habitat, so their designation did change to pine after they reached seven years.. All forest stands reverted to the youngest age-class after 140 years, simulating natural stand dynamics. Choosing stands for restoration was done using a random number generator. Stands were randomly chosen until 1500 ha of habitat was reached for each 10 year period. We allowed the final total at each time step to vary only by 5 ha in either direction, so differences between scenarios in the amount of habitat restored was minor (error bars are included but they are too small to be seen in Fig. 33b). Over the 50 year modeling horizon, overall pine increases from ~50% to ~64% of the landscape, closer to the 75% described in the 1827 reconstruction. Note that the forest configuration under the new BRAC implementation plan (assuming all BRAC areas are converted to open habitat) would move in a starkly opposite direction, with only 43% pine predicted (see Fig. 2b).

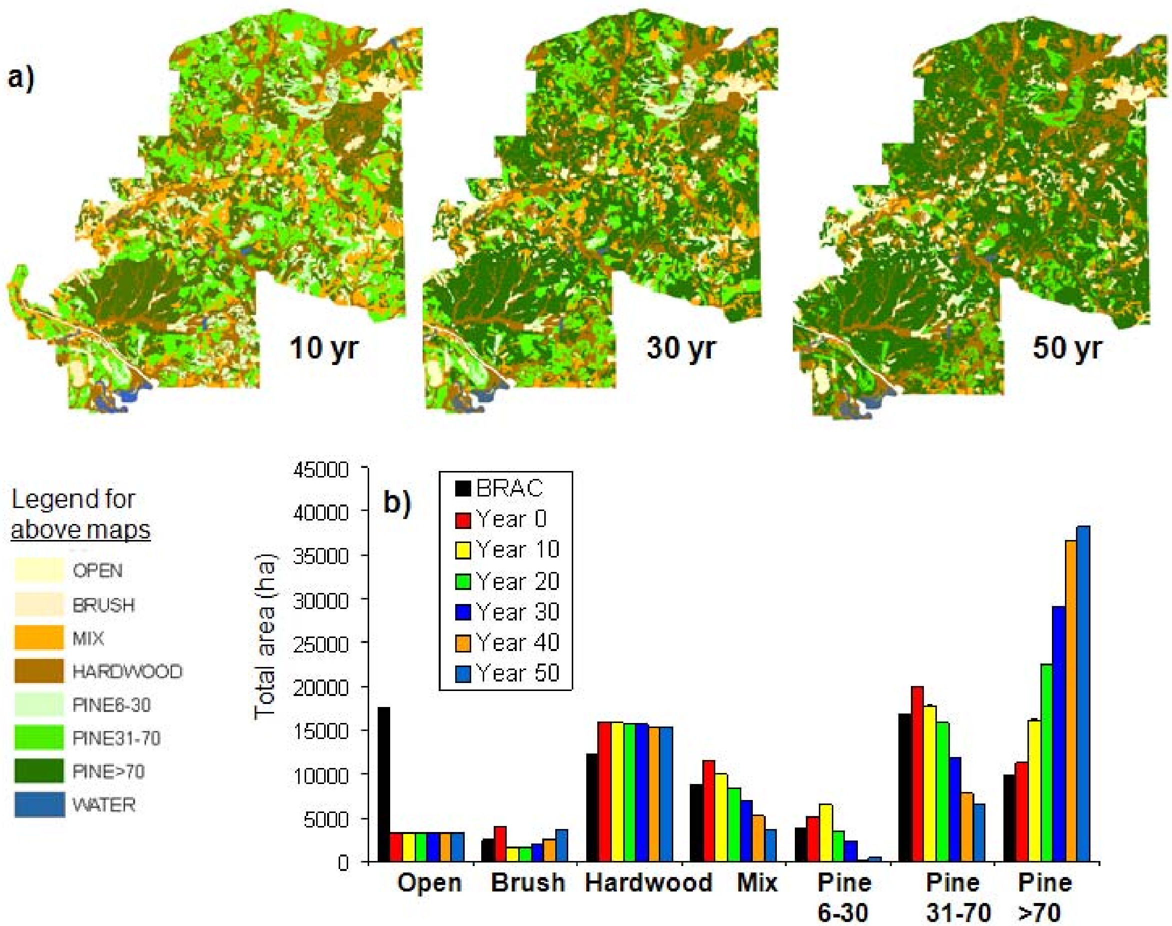


Figure 33. Stand composition of Ft. Benning under one realization of our simulated restoration plan at 10, 30, and 50 years (a). Mean area for each stand type (b) under all simulated maps at each time step (error bars are too small to be seen). Year 0 represents the current configuration and BRAC shows resulting composition after planned modifications (b). Maps of year 0 and BRAC configurations are shown in Fig. 2.

Unlike the road and BRAC scenarios, patch shape or size is not altered when designated for action. Therefore, analyses including patch loss were not included here (unlike in previous sections). Further, when running the EAM, we performed our summaries on maps that did not dissolve boundaries between two patches with the same habitat type. This is important because the patch summary statistics will only be calculated on the original patch area and not for the new configuration of the patch, which may have expanded if it happened to be restored next to a patch of the same class. This approach affects the interpretation of many patch statistics – because statistics only apply to a portion of the patch, but it is necessary if users want to track individual patches (as we did in this case). The EAM was implemented on the five replicate maps for each of the five time steps, the current (year 0) map and the BRAC map for a total of 27 scenarios run. All "pseudo-species" described above, including the edge species (EDSP) and the edge variants (A100, A200, T200, XT25, and XT50) were included in these simulations.

Results at the landscape scale show a similar overall shift between predictions of the EAM and the NULL models (Fig. 34) to those observed earlier. The results for the edge variants were nearly identical to earlier results with the biggest impacts seen only when the edge

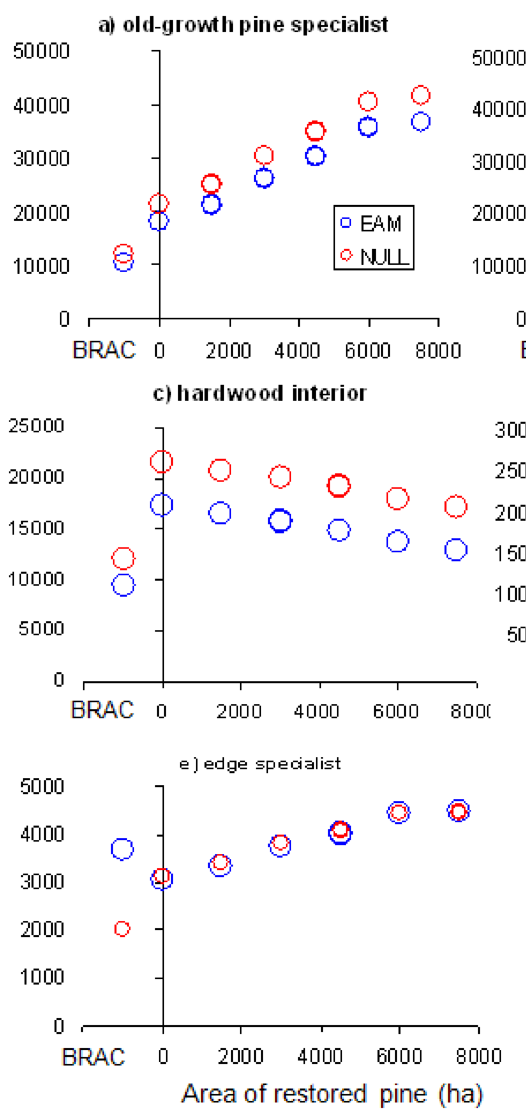


Figure 34. Total predicted population sizes for five target "species" as MIX stands are restored to pine (in 1500 ha increments) and the forest is allowed to age naturally. Time steps occur at 10 year increments. Predictions are from the EAM and a NULL model that ignores edge and context. Year 0 is the current forest configuration and the results for planned BRAC modifications are put in for reference.

responses are skewed (results not shown). Similar to the BRAC results, the trajectories of the EAM and NULL models were more parallel, suggesting that context has less of an impact relative to habitat change when integrated over the entire landscape. This was especially surprising for the old-growth pine specialist. This species avoids all edges with its most preferred habitat, so we suspected that as restoration continued (and the landscape was increasingly dominated by pine of increasingly older age classes), then the EAM would predict accelerated population gains. Instead, the NULL appears to gain slightly more quickly (Fig. 34a). This despite that, as restoration continues, the mean distance from edge increases in old-growth pine stands, the only main habitat type where this occurs (Fig. 35). On the other hand, as pine becomes more dominant on the landscape, then individuals are being added more quickly by the NULL model compared to the EAM (which always discounts population predictions by edge effects for this species). This means that the two models are predicting similar outcomes, but for very different reasons.

Another surprising result is that there is no difference in predictions for the edge specialist between the EAM and the NULL models (Fig. 34e). This is the only example we have seen of this pattern. The overlap was so extreme that we had to reduce the size of the NULL

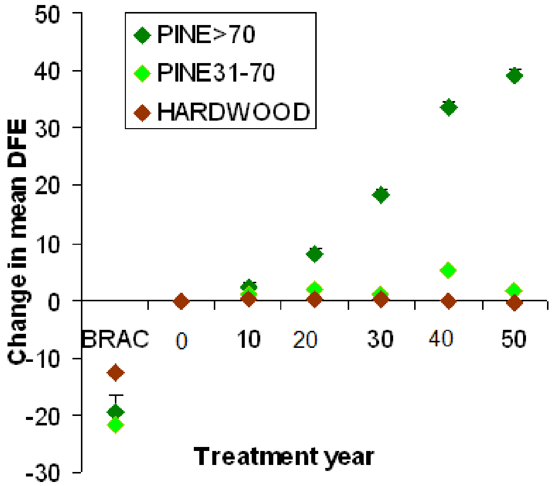


Figure 35. Mean difference in the mean distance from edge (DFE) for restored stands at each of five 10-year time steps. Predicted changes in DFE for the same stands under planned BRAC modifications are also shown.

symbols so that they could be seen. This result seemed especially surprising at first since this species is an extreme edge specialist. However, their preferred edge type is so rare on the non-BRAC landscape, this could account for the similarity in predictions for these scenarios. Indeed, under the BRAC modifications, the predicted population size is nearly twice as high as the NULL. BRAC modifications are predicted to have large, negative effects on all other species we modeled (including the two not shown). While pine species are predicted to do well under the restoration scenarios, hardwood species are predicted to decrease their population sizes, largely through the loss of MIX stands. While this may not be a conservation focus, most habitat-specific forest species on Ft. Benning are hardwood associates (Table 4), so these modifications could have significant negative impacts on that community.

Similar to earlier examples, there was a great deal of variability seen in patch-level predictions from the EAM (Fig. 36) unlike results summarized at the landscape-scale (Fig. 34). Variability was similar for the pine generalist and edge species, and the explanatory power of each factor is shown for all three species in Table 5. These results reinforce the importance of incorporating information about the quality of the edge response in patch metrics (i.e., Fig. 36d,e), especially when considering situations where edge responses are variable (Table 5). Threshold effects were only obvious in these scenarios when there was an upper boundary for predictions (i.e., Pine>70 in Fig. 35b). The variability in these results suggests that we should be able to maximize our restoration activities if we considered context when making restoration choices. This could be done via a process such as StopNGo mapping, or by using simple rules, such as "target for restoration stands that are near similar or even higher quality habitat."

Step 6: Management Recommendations

These demonstrations do not reflect any scenarios currently being contemplated by managers at Ft. Benning, so we do not have specific recommendations. Yet, our results suggest that sites for management action could be chosen in a way that could optimize potential benefits for target species. For instance, based on our results, it may be prudent to raise the conservation priority of hardwood patches surrounded by MIX rather than PINE or OPEN, because this configuration has the potential to further buffer habitat that is valuable for the many hardwood species on Ft. Benning. This group includes many migrants as well as those shown to be sensitive to edge and area. PINE may be resilient to actions that open it either internally or at its periphery. Finally, BRAC conversions are likely to lead to substantial changes in the bird community.

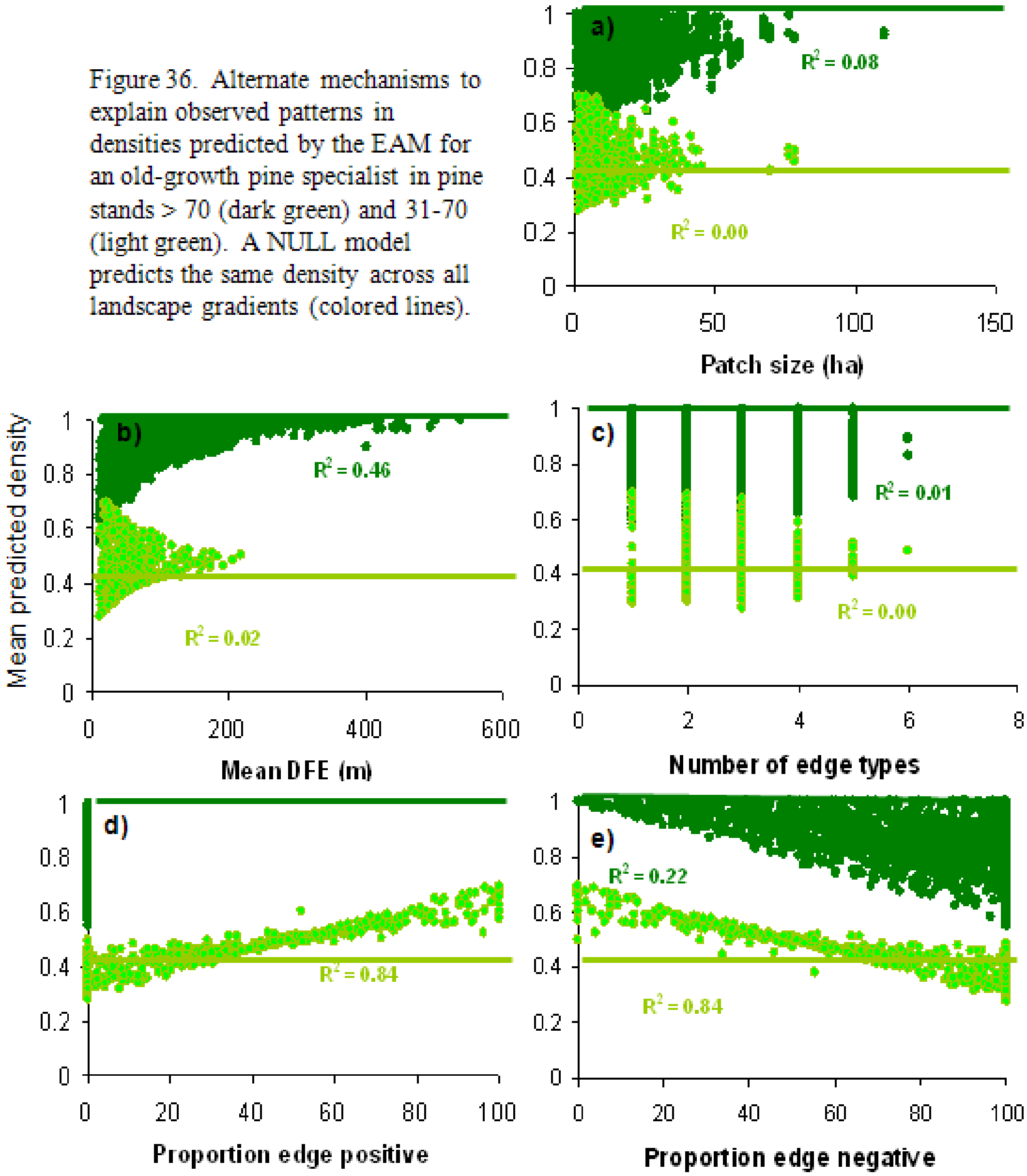


Figure 36. Alternate mechanisms to explain observed patterns in densities predicted by the EAM for an old-growth pine specialist in pine stands > 70 (dark green) and 31-70 (light green). A NULL model predicts the same density across all landscape gradients (colored lines).

Of course it is vital to recall that these predictions are made in the absence of empirical data characterizing actual edge and habitat responses on Ft. Benning. Based on the potentially strong influences of these drivers, we suggest that it is important to determine how pervasive edge effects are at the installation. Based on our results, it will also be important to know the shape of the edge response, and whether it is bilateral, or stronger on one side of the edge, either in the focal or adjacent habitat. This distinction had the largest impact on results, much more than the depth of edge responses, a more frequent measure of responses in the literature. Also important is determining the strength of forest-forest edge responses for birds. This is the most common edge type on Ft. Benning, although forest-open edges will become increasingly dominant in a post-BRAC landscape. The new data collection effort at Ft. Benning could efficiently parameterize the EAM and strengthen predictions to actual management alternatives. Based on the demonstration scenarios presented above, we suggest that management actions could be targeted to reduce negative impacts for multiple species if information on the spatial context of the affected habitat patches is taken into account. This could be done via a process such as StopNGo mapping and could lead to substantial improvement in conservation outcomes.

5.5 Results from the Ft. Hood Demonstration Project

Step 1: Identify Management Needs

We met several times with the managers at Ft. Hood. While much of our interaction focused on developing maps, working through their bird data, and presenting the results of our ecological analyses on bird responses to habitat and edges, we also worked with them to identify applications of the EAM that would be relevant to their management needs. We previously had presented our work from Ft. Benning on road density, and Ft. Hood managers agreed that a similar focus on roads and trails would be interesting and useful, although they suspected that most birds only responded to the largest roads, and were insensitive to edges created by smaller trails. They also doubted that any species associated with scrub (especially the BCVI) showed any edge-avoiding behavior. Finally, the managers at Ft. Hood were interested in the idea of developing scenarios to target habitat for restoration that balances the needs of the two target endangered species (GCWA and BCVI). In an October 2008 meeting, we developed a plan that our group would return during the fall of 2009 to present the results of the road modeling to the Ft. Hood managers. After that, the Ft. Hood team would help us develop specific restoration scenarios based on their management needs. Due to several scheduling conflicts, the meeting was not convened until later than planned (Dec. 18, 2009). At this meeting, the staff informed us that since our last meeting, Ft. Hood had decided not to actively choose habitat patches for conversion to BCVI habitat. Instead, they were planning to allow accidental fires (caused by live fire exercises) to maintain BCVI habitat within the live fire zone. This was partially due to the fact that with the current habitat configurations, they were meeting all their management targets for both species. Unfortunately, this made it very difficult for them to help us develop management scenarios. However, they told us that they were working on approaches to rate individual patches (currently based on size) for suitability. Based on that, we decided to focus on patch-based metrics and help develop a new rating system that incorporates edge effects and landscape context in predicting multiple species' responses, which can be used to weight habitat quality for future management decisions.

Step 2: Developing Edge Response Parameters

For both sets of scenarios (roads and restoration), we focused on GCWA habitat (WOODS) and BCVI habitat (SCRUB). Based on the results presented above (section 5.2), we are modeling edge responses of four species: GCWA, BCVI, BAWW, and BEWR. These species showed the most consistent and defensible patterns. However, other species showed patterns suggesting that they may experience important edge responses in this landscape as well (e.g., yellow-breasted chat, painted bunting, and northern cardinals). However, these results were inconsistent and relatively weak, so we did not model those species. It is important to note that these four species represent two groups with similar habitat associations – species associated with WOODS habitat (GCWA and BAWW) and species associated with mid-successional SCRUB habitat (BCVI and BEWR) (see Fig. 13). Species with broader habitat associations (such as NOCA and BGGN, see Fig. 13) were not modeled, nor were species associated with grasslands, for which we have no data. It is therefore important to remember that our modeling captures impacts for only a portion of the avian community on Ft. Hood.

Based on our focal habitat types (WOODS and SCRUB) and our cover classifications for the entire modeling area (red outline in Fig. 4a), we developed edge responses for six habitat pairs:
WOODS|OPEN
WOODS|SCRUB
WOODS|SCTREES
SCRUB|OPEN
SCRUB|SCTREES
SCRUB|WOODS

Based on the work presented in section 5.2, we used field data to parameterize four of these edge types (all WOODS edges and SCRUB|WOODS). For the two additional unstudied edges, we used our edge response model (Fig. 1c) to infer the most likely edge response direction, and then based edge response strength on similar edge types.

In addition to the edges listed above, we also needed to develop parameters for road edges, since one of our scenario topics focused on road density. In an effort to make our modeling relevant, we first determined how the local bird community responded to the roads and trails present on the landscape. Based on the placement of bird survey points, it was difficult to model distance to trails, since almost all points were located on a trail. However, we were able to determine if trails appeared to impact bird distributions by measuring bird detections relative to trail density within 50 m of each survey point. To determine the impact of trails (not roads) on habitat quality, we selected a subset of bird survey points that were at least 300m from any patch edge (including edges created by major roads) and determined how trail density impacted detection rates for GCWAs and BCVIs. As predicted by the Ft. Hood staff, there appeared to be no association with any measure of trail (not road) density and detection rates for GCWAs or BCVIs (Fig. 37).

Based on the above results, we ignored smaller roads and trails in our modeling and focused instead on major roads. Specifically, in developing our road map, we noticed that, in addition to paved roads, there was a class of unpaved road that created distinct edges on the

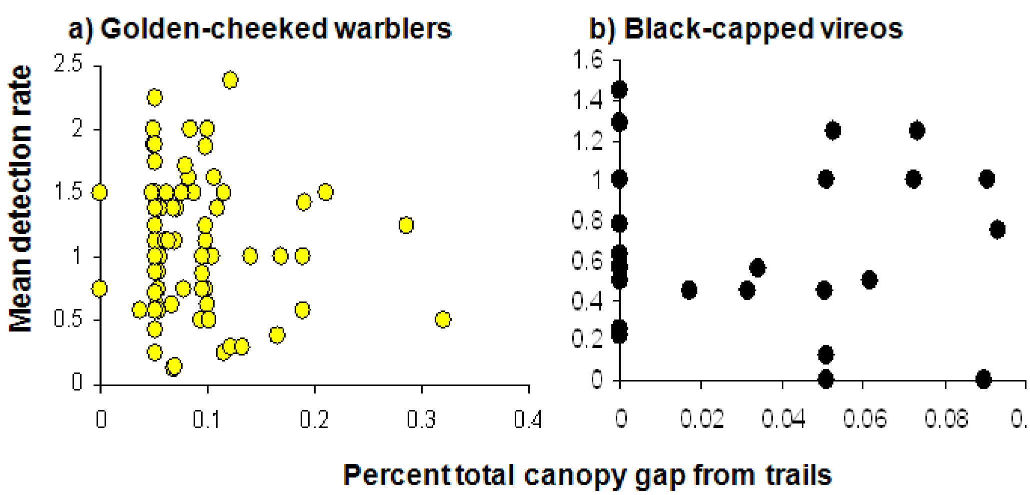


Figure 37. GCWA (a) and BCVI (b) do not respond numerically to the presence of trails. None of these points were within 300m of a bisecting road (or other edge type). Percent canopy gap refers to the loss of canopy due to trails within 50m of the survey point.

landscape (Fig. 38). These roads were consistently wide, had a bright surface, and were often continuous across focal patches. Because these roads appeared to bisect patches into fragments, we refer to them as bisecting roads (hereafter, BIROADS). This is in contrast to smaller roads and trails on the landscape that, while sometimes associated with large canopy gaps, did not appear to alter patch shape or continuity. Examples of trails and bisecting roads are shown in Fig. 38. In order to parameterize the EAM for our road scenarios, we needed to carry out an additional analysis at WOODS|BIROAD and SCRUB|BIROAD edges. Again, it was necessary to identify points at varying distances from BIROADS within WOODS and SCRUB habitat. We identified 23 points for WOODS|BIROAD edges and 21 points for SCRUB|BIROAD edges. We then ran Malcolm's model as described in Section 5.2.

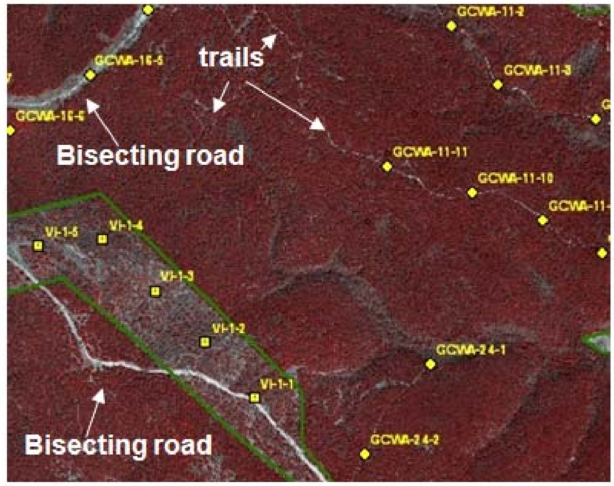


Figure 38. Roads and trails are ubiquitous throughout Ft. Hood and almost all bird survey points (shown in yellow) occur along them. Bisecting roads divide patches into distinct zones, while trails create internal heterogeneity.

The EAM requires estimates for four parameters: Dmin, edge density, Dmax, interior density (Fig. 5). We are currently using Malcolm's model to develop parameters for the EAM when field data are available (see section 5.2). Malcolm's model estimates a value (in our case, detection rate) as a function of four parameters: e0, D0, Dmax and k. Of the four model parameters, two are directly transferable to the EAM, Dmax and k (which is the same as the interior density). To use Malcolm's model to determine Dmin and the edge density, it is necessary to determine the density value at the edge. To do this, the "infinite.edge.effect" function (in the R-package "edgefx") is used to calculate the density when d=0 (using the parameters returned by the analysis). If the predicted density is greater than 0, then Dmin = 0 and the edge density is whatever value was returned. If the returned value is less than 0, then it is necessary to determine the distance, d, where the predicted density is 0. That value for d can be interpreted as Dmin and the edge density is set to 0. It is important to stress that the Malcolm parameter D0 is not analogous to the EAM parameter Dmin (although they are related). When D0>0, a non-linear relationship near the edge is expected, even if the edge density is greater than 0. This shape can be captured by using Dmin to indicate where edge densities begin to level off as the edge is neared. However, when we employed model selection theory to distinguish among a suite of candidate models, we never found support of a model where D0>0 for our data, so we did not address that issue in depth.

In developing parameters for the EAM, we also had to grapple with the restriction that the interior density should always be the same when species and focal habitat are held constant. For instance, GCWA within WOODS habitat should have the same interior density at all four edge types (OPEN, SCRUB, SCTREES, BIROAD). Because edge responses are estimated from completely independent data for all four edge types, it is unlikely any of the four separate models would return the *exact* same interior density (k). Further, when data are highly variable as they are at Ft. Hood, multiple models converge on a variety of parameter combinations that lead to moderate to substantial variability in the estimates for k. However, model predictions tend to be more similar within the edge zone (see Figs. 15 and 16). To ensure that interior densities are always consistent when species and focal habitat are held constant, we used a combined method of choosing candidate models that converge near the same interior density (k). To make final adjustments, we modified Dmax while holding e0 constant until values of k converged exactly. This allowed us to meet our assumption of equal values of k between edge types within the same focal habitat, while introducing only a minimal impact on the predictions within the edge zone.

For the four focal species, we began by choosing the best model for each species-edge type combination (the model with the lowest AIC score). But when models returned parameters for k that were very different within the same focal habitat type, we selected, when available, a different, closely ranked model (within 2 AIC points) that predicted a more similar value of k. In order to meet our assumption of having equal interior densities within the same habitat type, we then determined the value of Dmax (assuming the same e0) that gives the desired interior density value (using the “infinite.edge.function” in the “edgefx” R-package). To determine edge density and Dmin, we used the same function to determine the density at the edge. If the model reached 0 density, we determined the distance at which this occurred, and used that as Dmin in our model. This occurred consistently for the BAWW and at SCRUB|BIROAD edges for the BEWR. Neither the GCWA nor the BCVI reached zero density at the edge. This suggests that individuals are “spilling over” from preferred habitat into adjacent lower quality habitats. Unfortunately, there were insufficient data in non-habitat to develop edge response parameters using Malcolm’s model. So, in these cases, we estimated spillover functions based on visual inspection of the data, but also assuring edge densities were equal for the same edge types. The output from Malcolm’s models and the final parameters developed for the EAM are shown in Table 6.

It is clear from this exercise that developing these parameters still relies on experience and some interpretation on the part of the EAM user. This is partly due to the high variability in Ft. Hood data. Ecological data tend to be “noisy” in general, so this problem may be a persistent one. However, the problem here was exacerbated by a survey design that was not intended to estimate edge response functions. The fact that the Malcolm model converged on multiple solutions for several (but not all) species/edge type combinations is indicative of the variability in these data. However, while models were variable in their convergence on Dmax and k, behavior near the edge was largely consistent for most of the parameter combinations. In reality, our evidence for Dmax and k were weakest when we were forced to choose low-ranked models in order to “force” k to converge for multiple edge types. This was true in only a few cases (where delta AIC is greater than 2). The worst case was for BEWR (see Table 6). The best models for this species always chose Dmax far beyond the range of our data, which indicates that Dmax may not have been reached within the range of field sampling. Despite having to grapple with multiple models, the comparison of AIC values and final parameters shows that model tweaking (to meet our assumption of equal values of k within the same habitat) was kept to a minimum and often had a minimal effect on the final parameters. Ultimately, despite the adjustments made, this approach is still far less subjective than past ones, and is likely to be more objective and easier to implement in situations where the field sampling designs were more appropriate for model parameterization.

Table 6. Parameters from three competing models to measure edge effects (DNC, INFINITE, COMPLEX) which will be compared to a NULL model. The models with the lowest AIC score indicates the "best" model based on data fit and number of parameters.

			MODEL BUILD RESULTS				EAM PARAMETERS			
Edge Type	Year	Model	e0	Dmax	k	ΔAIC	Dmin	Edge Dens	Dmax	Int Dens
Golden-cheeked warbler (GCWA)										
WOODS|OPEN	Mean	COMPLEX	-0.0028**	314***	1.04***	**0.00**	0	0.16	314	1.04
WOODS|SCRUB	Mean	COMPLEX	-0.005	203**	1.08***	**0.00**	0	0.10	188	1.04
WOODS|SCTREES	Mean	COMPLEX	-0.0014	402*	1.14***	**0.607**	0	0.60	315	1.04
WOODS|BIROAD	Mean	COMPLEX	-0.0015	218	1.08***	2.746	0	0.77	180	1.04
SCRUB|WOODS	Mean		Parameters from visual inspection				0	0.10	150	0
Black-capped vireo (BCVI)										
SCRUB|WOODS	Mean	IDEAL	-0.0021	179	0.84	2.724	0	0.47	130	0.74
SCRUB|BIROAD	Mean	COMPLEX	-0.0010	343'	0.74***	**0.830**	0	0.40	343	0.74
WOODS|SCRUB	Mean		Parameters to match Woods density				0	0.47	50	0
Black-and-white warbler (BAWW)										
WOODS|OPEN	2005	COMPLEX	-0.0025	195*	0.45***	**0.00**	28	0.00	110	0.23
WOODS|SCRUB	Mean	COMPLEX	-0.0026	128	0.23***	**1.67**	49	0.00	128	0.23
WOODS|SCTREES	Mean	COMPLEX	-0.0035	135**	0.26***	**0.39**	60	0.00	120	0.23
WOODS|BIROAD	Mean	COMPLEX	-0.0026	128	0.26***	1.297	31	0.00	110	0.23
SCRUB|WOODS	Mean		Parameters from visual inspection				0	0.00	0	0
Bewick's wren (BEWR)										
SCRUB|WOODS	Mean	IDEAL	-0.0037	180*	0.63***	13.738	0	0.08	120	0.42
SCRUB|BIROAD	Mean	COMPLEX	-0.00944	89'	0.42***	2.34	47	0.00	89	0.42
WOODS|SCRUB	Mean		Parameters from visual inspection				0	0.08	400	0

'p<0.10, *p<0.05, **p<0.01, ***p<0.0001

Steps 3-5: Scenario Modeling on Ft. Hood with the EAM

We developed and ran models on two sets of scenarios at Ft. Hood: road and restoration scenarios. We present the results for the next three steps (developing scenarios, running the model, and analyzing results) grouped by scenario type.

<u>Road Scenarios</u>

In addition to its use in developing edge response parameters (see step 2 above), the road and trail map that we developed (Fig. 4b) was used as a basis for our modeling the impacts of road density. As before, we focused on a section of the base for our simulation of differing road densities (see red outline in Fig. 4a). Because this section of the base has one of the lowest densities of roads overall, our modeling focused only on adding, and did not include iteratively deleting roads, although we included a scenario map with all roads removed. The current network of bisecting roads in the modeled section is 67km long. We developed additional maps with aggregated road lengths of 0, 100, 150, 200, 250, 300, 350, and 400km (Fig. 39). Five replicate maps of the 100 to 400km road lengths were made.

We assumed two widths for bisecting roads when intersecting them with the habitat map. Most bisecting roads were set to be 20 m wide, which was a typical width observed on Ft. Hood. However, we also identified some roads as “vireo” roads. These were roads that were particularly wide (50m) and had developed into vireo habitat (according to Ft. Hood habitat maps). One possibility for future road modeling is to model these widest road gaps to have vireos in them. At this time though, we did not include that outcome in our modeling parameters. The 37 road scenario maps (examples Fig. 39) were intersected with the modeling area of the habitat map (Fig. 4a) to create the maps used to implement the EAM. The EAM was then parameterized using the parameter estimates listed in Table 6. Output was summarized at both the landscape and patch scales.

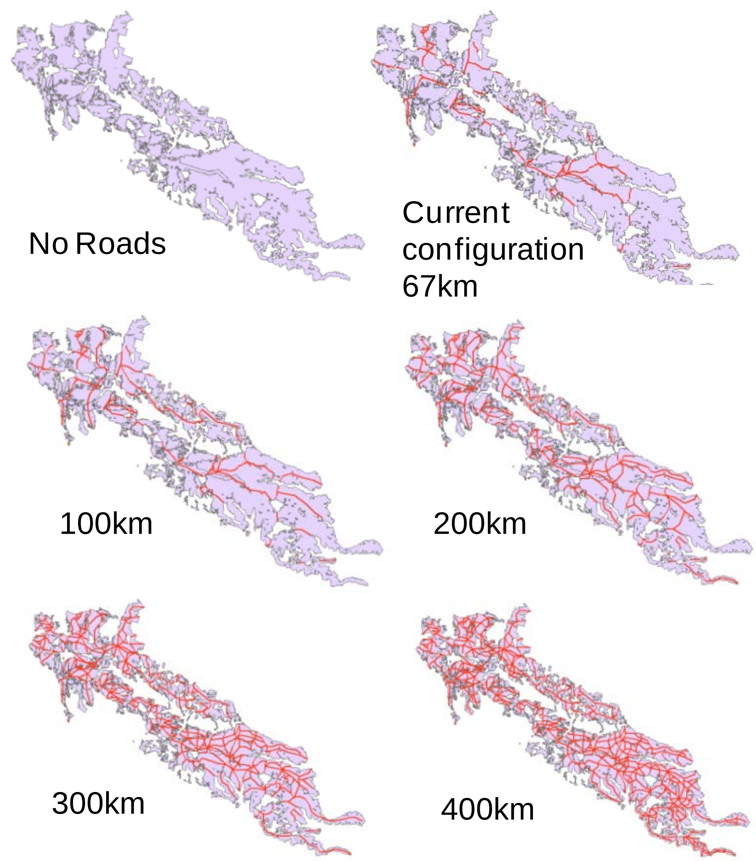


Figure 39. Examples of road density scenario maps for the portion of Ft. Hood used for modeling (see Fig. 4a). Roads were added in 50km increments (except to reach 100km) to 400km; 150, 250, and 350km density maps are not shown.

Results at the landscape

scale are similar to those found at Ft. Benning (Fig. 40), yet they also show interesting differences. The typical “shift” between the EAM and NULL predictions was only observed for GCWA and BAWW. BCVI and BEWR had similar predicted population sizes when road densities were low, with the EAM predicting a higher overall population for the BCVI when roads were absent (Fig. 40b). This change in pattern was due to the fact that, in estimating EAM parameters, we allowed spillover into non-focal habitats (unlike model runs at Ft. Benning). This spillover compensated, in non-focal habitat, for loss of individuals near edges within focal habitats. GCWA also had spillover included in its parameters (Table 6), but evidently it was not enough to compensate for the extreme edge responses for this species at most edges. In fact, GCWA showed an interesting pattern in that, as road density increased, the EAM actually showed a slight (almost imperceptible) increase in population compared to the NULL, which continues to decline (Fig. 40a). This happened because GCWAs show their weakest edge responses to roads. As roads come to dominate the landscape, the overall edge effect to other edge types weakens.

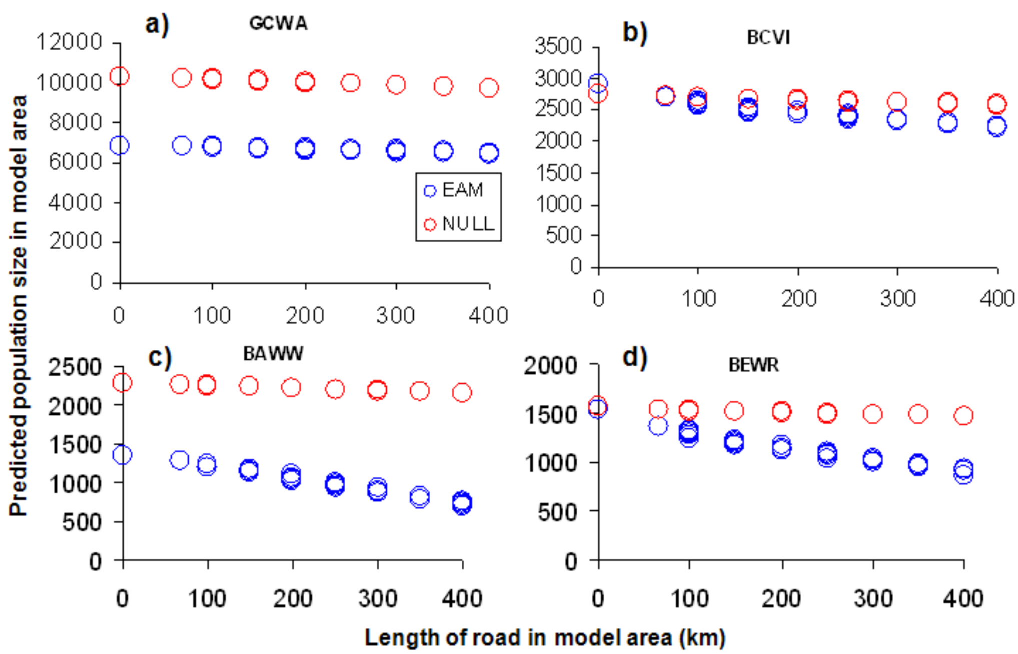


Figure 40. Predicted population sizes in replicate scenarios that modeled different road lengths in a select area in Ft. Hood (Fig. 39) for four species (a-d).

Similar to our other modeling efforts at Ft. Benning, there was very little difference in predictions between the replicate scenarios (notice minimal scatter between points at the same road density levels in Fig. 40). This suggests that differences between replicate road networks are lost as stronger and weaker local effects are averaged across the landscape. However, the same degree of patch-level variability in responses indicates that patch context has the potential to either compensate for or exacerbate the negative impacts of road development (Fig. 41). Similar to other modeling results, we show evidence for thresholds and strong patterns in variability across a fragmentation gradient (Fig. 41). Results exploring the most important metrics showed both similar and some different patterns from those of Ft. Benning (Table 7). All four species often had strong relationships with simple patch metrics, and distance from edge was especially strong in its association with predicted density. In fact, for species that avoid all edges (GCWA and BAWW) simple patch metrics were more powerful predictors than the more

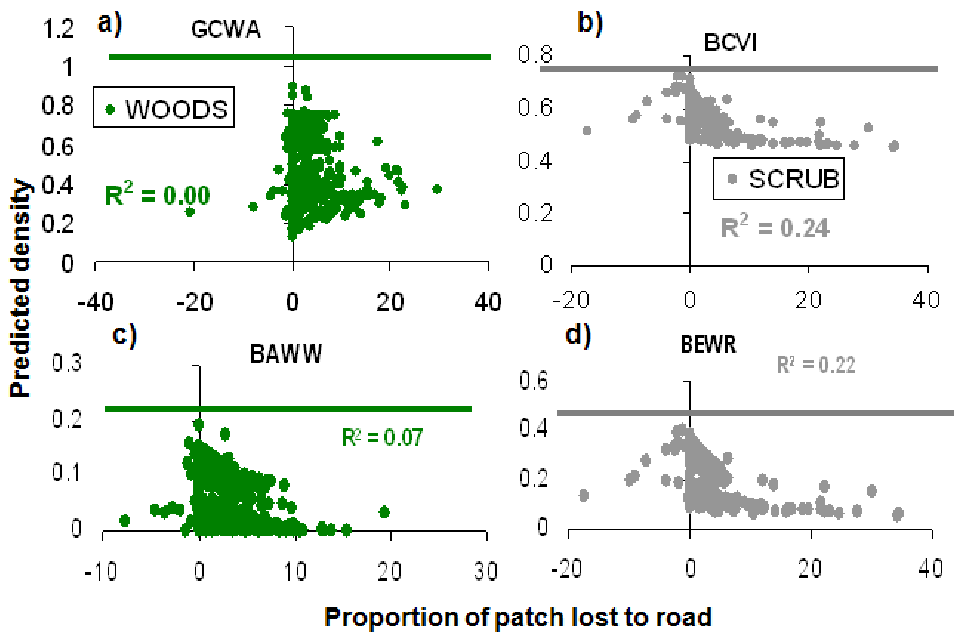


Figure 41. Predicted density for all unique patch configurations in the replicate model landscapes for four species based on predictions of the EAM. NULL predictions, constant across patch configuration, are shown with colored lines.

computationally intensive measure of the proportion of negative edges. This indicates that for extreme edge avoiders (such as many endangered species), simple metrics may suffice for understanding context and edge responses at the landscape scale.

Table 7. Explanatory power of each landscape variable on Ft. Hood

Species	habitat	summary	Explanatory variable	Road
GCWA	WOODS	Avoids	Prop patch lost	0
	WOODS	all edges	**Patch area**	**0.26**
	WOODS		**Distance from edge**	**0.52**
	WOODS		**No. edge types**	**0.57**
	WOODS		Prop edge positive	na
	WOODS		Prop edge negative	0.24
BCVI	SCRUB	Avoids	Prop patch lost	0.24
	SCRUB	some edges	Patch area	0.12
	SCRUB		**Distance from edge**	**0.48**
	SCRUB		**No. edge types**	**0.36**
	SCRUB		Prop edge positive	na
	SCRUB		**Prop edge negative**	**0.81**
BAWW	WOODS	Avoids	Prop patch lost	0.07
	WOODS	all edges	**Patch area**	**0.29**
	WOODS		**Distance from edge**	**0.64**
	WOODS		**No. edge types**	**0.37**
	WOODS		Prop edge positive	na
	WOODS		**Prop edge negative**	**0.29**
BEWR	SCRUB	Avoids	Prop patch lost	0.22
	SCRUB	some edges	**Patch area**	**0.28**
	SCRUB		**Distance from edge**	**0.66**
	SCRUB		**No. edge types**	**0.58**
	SCRUB		Prop edge positive	na
	SCRUB		**Prop edge negative**	**0.73**

Restoration Scenarios

In this application of the EAM, we focus on measuring patch quality based on several criteria. Therefore, this section differs from the scenario-based analyses described in other examples that compared the habitat value of one or more patches under different management scenarios. The only “scenario” aspect of this exercise is that one of our considerations is the impact of converting each of the focal patches to its alternate habitat type (i.e., converting SCRUB to WOODS or vice-versa) and how that would impact each of the species under consideration. We undertook this series of analyses because, despite the many advances in understanding how landscape structure alters habitat quality, many managers still must assess patch quality for a host of management objectives, and they are often constrained to using only the simplest of metrics (usually size and sometimes shape) in trying to compare the habitat quality of specific sites they are managing. In the case of Ft. Hood, managers are currently assessing management priorities based largely on patch size (in the form of rankings). We offered to show how incorporating information on patch shape and context, and their influence on multiple species, could be used to further evaluate management priorities.

To do this, we identified patches of GCWA habitat (“WOOD”, see above) and BCVI habitat (“SCRUB”) within our modeling area of Ft. Hood (see red outline in Fig. 4a) for consideration. In addition, we modeled responses of two species that are also strongly associated with these two main habitat types, BAWW in WOOD and BEWR in SCRUB. To limit consideration to those patches that might be meaningful for conservation, we considered only patches >1ha. In the original model area, there are 30 SCRUB patches and 94 WOOD patches that meet this size criterion. We therefore decided to focus on 30 patches of each type. We used all 30 patches of SCRUB habitat, and then chose 30 of the 94 patches of WOOD habitat at random. The targeted 60 patches are shown in Fig. 42, and several patch metrics are described in Table 8.

Initially, we used several different metrics to gauge the quality of each of the 30 WOOD and 30 SCRUB patches and compare the different metrics. These metrics, shown in Table 8, relate only to patches and their structure, not species-level responses, which we consider later. This table describes, for each of the 60 patches, typical landscape metrics (excluding connectivity). This includes size of the habitat patch, the mean distance to edge (which is generated by the EAM), and a typical shape index (from Patton 1975). The shape index indicates how much each patch deviates from a circle (the geometric shape that minimizes the perimeter-to-area ratio).

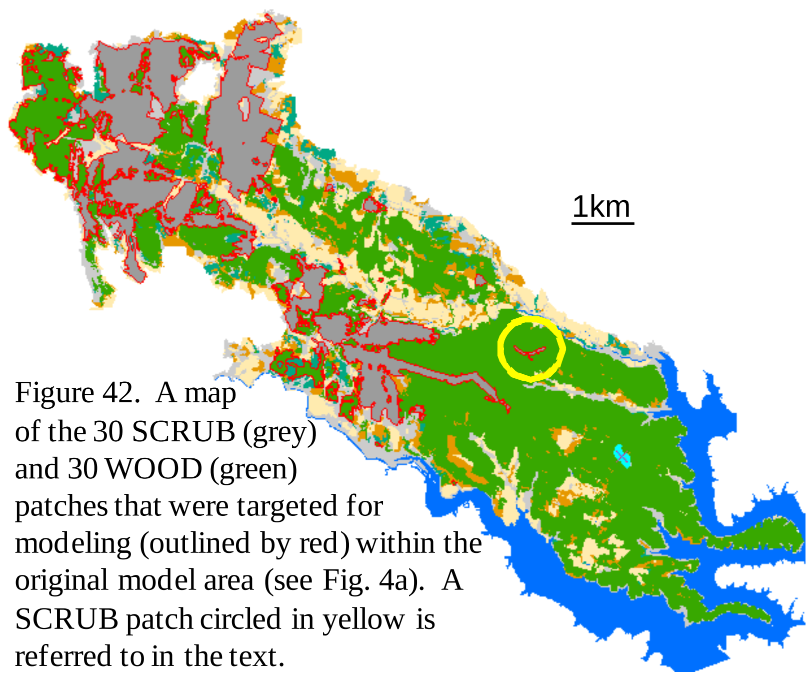


Figure 42. A map of the 30 SCRUB (grey) and 30 WOOD (green) patches that were targeted for modeling (outlined by red) within the original model area (see Fig. 4a). A SCRUB patch circled in yellow is referred to in the text.

Table 8. Patch descriptors for 30 Scrub and 30 Wood patches used for modeling habitat quality at Ft. Hood (see Fig. 42). Values in final two columns are if the habitat were converted to an alternate type.

Patches in Scrub (BCVI habitat)	Area (ha)	Shape Index*	Mean Edge Dist (m)	Number Edges	Surrounded by Scrub	Surrounded by Woods	Mean Edge Dist (m)+	Number Edges+
ScrubVI_2097	903.3	3.31	184.2	8	46%	54%	207.0	7
ScrubVI_2096	1473.8	7.22	148.3	7	22%	78%	280.5	7
ScrubVI_2095	5.8	1.16	35.4	3	3%	97%	91.1	3
ScrubVI_2093	16.4	2.25	35.6	3	4%	96%	146.3	4
ScrubVI_2091	2.4	1.51	21.0	1	0%	100%	175.3	3
ScrubVI_2087	16.6	1.66	42.3	3	0%	100%	132.8	4
ScrubVI_2085	276.7	4.54	86.2	6	15%	85%	149.5	6
ScrubVI_2084	3.7	1.57	20.3	5	25%	75%	22.1	4
ScrubVI_2083	5.0	1.32	29.0	4	73%	27%	36.0	3
ScrubVI_2081	10.7	2.05	30.6	4	4%	96%	68.5	6
ScrubVI_2080	17.7	1.40	60.9	3	58%	42%	77.4	3
ScrubVI_2078	2.3	2.03	11.5	3	19%	81%	38.7	3
ScrubVI_2077	1.1	1.33	12.7	2	27%	73%	37.4	3
ScrubVI_2074	1.1	1.56	12.7	2	16%	84%	37.7	3
ScrubVI_2072	3.2	1.54	20.1	3	10%	90%	37.6	4
ScrubVI_2070	8.0	1.69	29.8	2	1%	99%	172.1	5
ScrubVI_2069	174.3	3.51	87.2	7	37%	63%	138.8	7
ScrubVI_2068	10.9	1.16	50.6	3	20%	80%	125.8	2
ScrubVI_2067	1.6	1.52	14.5	3	20%	80%	49.7	2
ScrubVI_2066	5.5	1.47	27.9	4	71%	29%	38.2	3
ScrubVI_2065	728.8	5.60	103.0	7	19%	81%	398.7	7
ScrubVI_2064	2.6	1.93	12.0	1	0%	100%	122.9	2
ScrubVI_2063	1.5	1.30	15.0	1	0%	100%	73.0	1
ScrubVI_2060	1.4	2.05	8.0	2	0%	100%	49.2	2
ScrubVI_2058	17.0	2.44	29.9	6	40%	60%	49.0	5
ScrubVI_2056	11.7	2.66	19.0	1	0%	100%	795.0	1
ScrubVI_2055	3.4	2.06	15.9	4	18%	82%	23.4	3
ScrubVI_2053	11.7	2.42	26.2	2	16%	84%	108.9	3
ScrubVI_2052	1.1	1.59	11.0	3	93%	7%	10.8	2
ScrubVI_2051	12.9	1.59	38.0	3	43%	57%	88.3	2

Patches in Wood (GCWA habitat)	Area (ha)	Shape Index*	Mean Edge Dist (m)	Number Edges	Surrounded by Scrub	Surrounded by Woods	Mean Edge Dist (m)+	Number Edges+
WoodsWA_2581	15.8	2.99	21.7	6	69%	31%	27.9	6
WoodsWA_2580	748.8	5.97	111.1	7	53%	47%	122.9	7
WoodsWA_2579	26.7	2.57	36.1	4	17%	83%	161.4	4
WoodsWA_2578	26.6	3.13	31.1	3	5%	95%	186.7	5
WoodsWA_2576	1.1	2.24	6.8	3	21%	79%	20.7	2
WoodsWA_2575	3.3	1.30	24.8	2	0%	100%	61.7	2
WoodsWA_2567	1.1	1.24	14.0	1	0%	100%	102.0	1
WoodsWA_2564	13.2	2.25	28.7	6	14%	86%	118.6	6
WoodsWA_2563	1.5	1.36	14.0	1	0%	100%	95.0	1
WoodsWA_2560	2.2	1.57	16.6	5	40%	60%	22.0	4
WoodsWA_2555	1.3	1.22	14.8	2	24%	76%	14.8	2
WoodsWA_2546	16.5	2.12	36.0	5	22%	78%	85.3	4
WoodsWA_2545	1.2	1.37	13.9	3	0%	100%	24.8	2
WoodsWA_2540	7.7	2.35	18.6	4	9%	91%	23.3	4
WoodsWA_2539	1.6	1.81	10.7	4	44%	56%	10.7	4
WoodsWA_2521	4.1	2.28	18.5	4	57%	43%	18.5	4
WoodsWA_2520	2.6	2.23	11.7	3	0%	100%	70.9	3
WoodsWA_2517	1.7	1.08	21.0	2	86%	14%	21.0	2
WoodsWA_2514	23.0	2.26	44.8	6	23%	77%	49.0	5
WoodsWA_2512	4.8	1.79	19.7	4	78%	22%	19.7	4
WoodsWA_2511	5.2	2.43	16.6	6	51%	49%	17.8	5
WoodsWA_2507	1.7	1.46	14.0	1	0%	100%	122.6	2
WoodsWA_2501	100.9	3.95	48.8	6	74%	26%	51.1	5
WoodsWA_2489	6.2	2.34	20.4	3	37%	63%	59.1	3
WoodsWA_2488	2.7	1.69	17.9	3	85%	15%	17.9	3
WoodsWA_2487	20.8	2.67	31.2	5	52%	48%	31.2	5
WoodsWA_2485	41.4	2.54	46.5	4	70%	30%	46.5	4
WoodsWA_2484	1.9	1.48	15.0	1	0%	100%	250.3	2
WoodsWA_2479	2.0	1.46	16.3	4	49%	51%	16.3	4
WoodsWA_2475	1.7	1.16	19.5	3	90%	10%	19.5	3

* Shape Index from Paton (1975) and describes deviation in shape from a perfect circle (1)

+ Values if patch was converted to other main habitat type (i.e., Scrub to Woods or vice-versa)

The mean distance to the nearest edge is related strongly to patch size, but also captures some aspects of shape (Fig. 43a); however these relationships can be hard to disentangle. The shape index may be independent of size, but in practice it is often related (as shown in Fig. 43b). In this case, larger patches have more complex shapes, thus they experience greater edge influences than would be expected, based on area alone. Where patch shapes are highly irregular, they may experience greater "edge effect" than a smaller patch that more closely approximates a circle in shape. When patch shape is held constant, larger patches have *less* edge influence, as is indicated by mean distance to edge (Fig. 43a). This means that both size and shape metrics, when considered independently, leave out important information about relative edge influence.

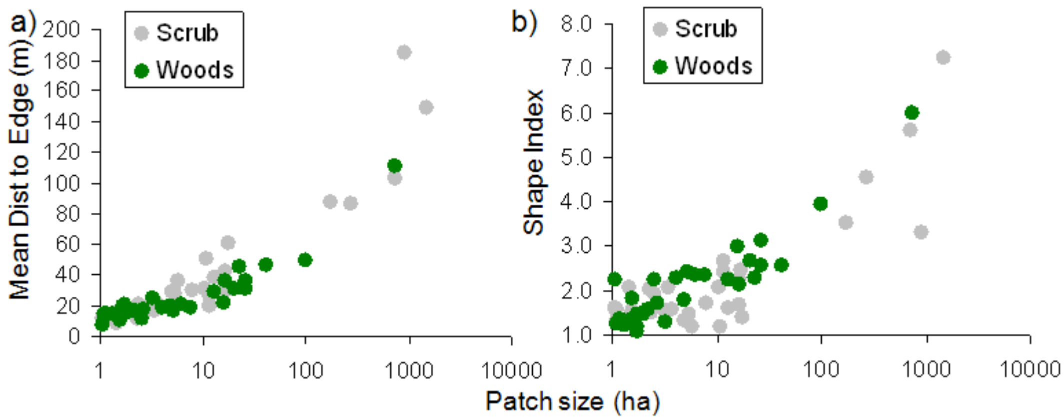


Figure 43. The relationship between patch size and mean distance to edge (a) and shape (b) for 30 Scrub and Wood patches. Shape Index relates how much a patch deviates from a perfect circle (shape index of 1), that minimizes edge to area ratio.

Of course, considering size and/or shape as proxies to edge influence is further complicated by the varying influence of different edge types, integrated over the entire patch. Indeed, when looking at the quality of the surrounding habitat, the relationship with size may weaken or disappear entirely. For instance, patch complexity, expressed as the number of edge types per patch, shows a weaker relationship with size than do distance to edge or shape (Fig. 44a). While it makes sense that larger patches tend to have more edge types, a surprising number of smaller patches are embedded in very complex habitat as well. It is worth noting that, in this Ft. Hood landscape, the vast majority of patches are surrounded by three or more different edge types, in contrast to a traditional view of "edge" as a uniform habitat class (Sisk and Battin 2002). Of course, landscape complexity has a varying impact on species response (Table 7). Because we are still considering only landscape structure, we also looked at the proportion of each patch that was surrounded by a high-contrast type. In Ft. Hood, most of the species we have considered are habitat specialists and, therefore, tend to avoid edges with non-habitat, so this metric may be instructive. The proportion of habitat that is not high-contrast is largely made up of habitat with a similar structure to the focal patch that has nevertheless been identified by Ft. Hood ecologists as unsuitable habitat for their two target species (i.e., BCVI in SCRUB and GCWA in WOODS). For this metric, there is no relationship with patch size (Fig. 44b).

Another interesting factor to consider is how mean distance to edge changes when the target patch is converted to a different type (i.e., from SCRUB to WOODS, or vice-versa). This is shown in Table 8 by comparing the columns both labeled Mean Edge Dist – the second column (with a "+") indicates what the metric would be under the conversion scenario. Some of the changes are quite dramatic. For instance, the SCRUB patch "ScrubVI_2056" changes from

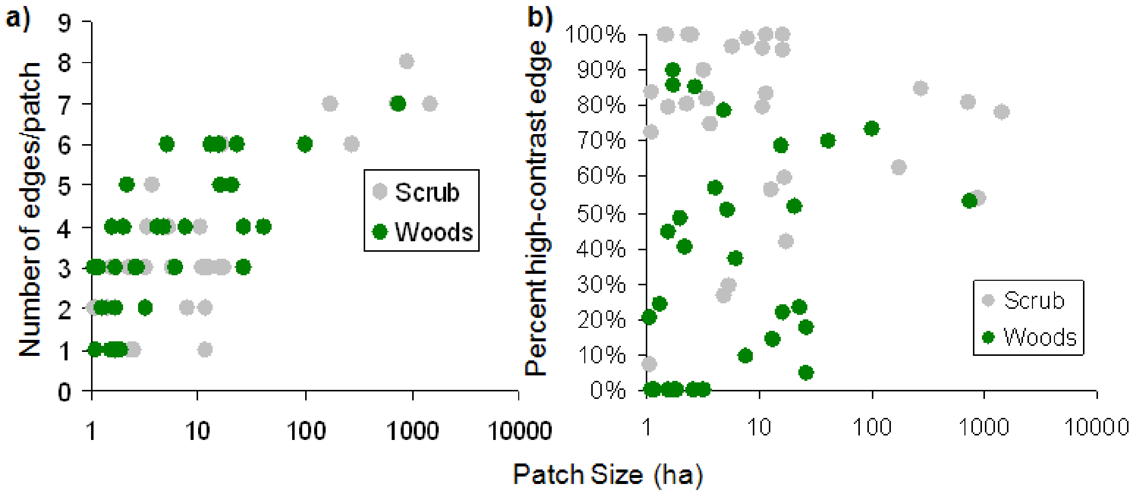


Figure 44. The relationship between patch size and the number of edge types per patch (a) and the percent of surrounding habitat that is "high contrast" (b) for 30 Scrub and Wood patches.

having a mean distance to edge of 19m to 795m if the patch were to be converted to WOODS habitat. This is because this small, sinuous SCRUB patch (circled in yellow Fig. 42) is embedded in a very large patch of WOODS. Based on the emerging principles of "edge ecology", one could imagine that if this patch were allowed to succeed to WOODS, then the newly interior nature of the habitat would allow for higher densities of GCWAs (and other late-successional species like BAWWs), both in the patch itself and in the surrounding habitat, which under the current configuration is likely to be strongly influenced by the edge. Although this is an extreme case, many other patches show a doubling or even quintupling of edge distance – and some other extreme cases can be noted (e.g., for "WoodsWA_2484" Mean Edge Dist changes from 15m to 250m if converted to SCRUB). Both these and other examples show that converting small patches could add substantial "interior" habitat back into the landscape at minimal cost, and could emerge as conservation priorities. It is also a reminder that decisions about management can influence not just the target patch, but the surrounding habitat as well.

Of course, to consider actual ecological impacts of landscape design and habitat management, it is important to look at the predicted consequences on specific species of interest in the landscape – and how those species might be impacted by management decisions. To do this, we used the EAM to generate predictions for distributions of four species: BCVI and BEWR, both associated with SCRUB habitat, and GCWA and BAWW, both associated with WOODs habitat. We used the same parameters discussed earlier for these four species. We ran the EAM on each patch under two management scenarios. In the first scenario, we maintained the current patch designation (SCRUB or WOODS). In the second scenario, we assumed that each of the patches had been converted, through management actions, to the other focal habitat type (i.e., SCRUB converted to WOODS or vice-versa). Because patch type has an obvious impact on adjacent patches, we ran multiple conversion scenarios so that results were calculated separately, as if each patch was the only patch that was converted in the landscape (for that particular run). The results of each run were then summarized in two ways. First, using only data drawn from the patch that was converted and, second, by summarizing effects over a 500m buffered area (since some spillover extends up to 400m). These four ways of generating data with the EAM (two conversion scenarios, two approaches to summarizing results) were completed for each of the four target species listed above, in each of the 60 patches.

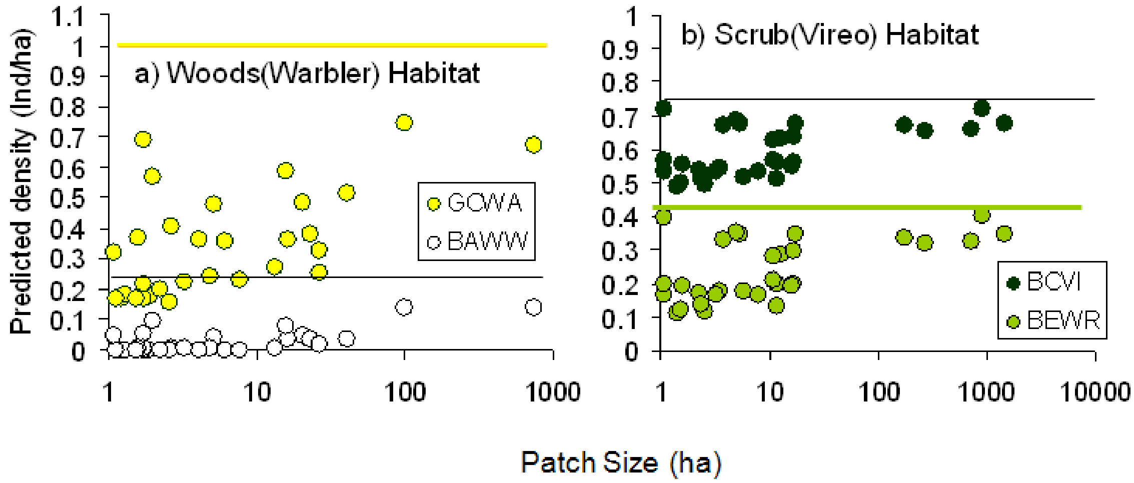


Figure 45. The relationship between patch size and predicted densities for species associated with Woods habitat (a) and Scurb habitat (b). The colored lines indicate the NULL predictions for patch density which do not vary by size or context.

The predictions of the EAM show how the consideration of patch size alone can give a misleading indicator of habitat value for a given patch, especially if considered on a per hectare scale (Fig. 45). For instance, the mean density of the GCWA varies greatly among the 30 patches, and it is always below the "null" density, the predicted value if edge responses are ignored (Fig. 45a). Although there is a relationship with size, it is a weak one, and there are large differences in predicted densities, even among the smallest patches. This suggests that those patches have very different values for the target populations. Interestingly, many of the patches were predicted to be too small to support viable populations of BAWW, with predicted densities near zero for many patches, excepting only the largest. Edge responses, which were overall weaker for BCVI and BEWR, showed a shallower relationship with patch size and predicted density (Fig. 45b). However, this may be due, in part, to a lack of information, as we were only able to model responses at WOODS and ROAD edges. Because information was unavailable for other edge types (i.e. open), we assumed a neutral response at those edges. The similarity in response between BCVI and BEWR reflects the similarity of their responses at both edges that we had data for, whereas responses for GCWA and BAWW differed to a much greater extent. However, for all species, these results illustrate that different patches are of different value for different species – even if the habitat type remains consistent – due solely to edge effects.

Another interesting factor to consider is the effect of converting a patch to a contrasting type. In the case of Ft. Hood, the key habitat types (SCRUB and WOODS) are different successional stages of the same Oak-Juniper vegetation alliance. Therefore, there is a trade-off between managing for one or the other habitat type, and that tradeoff will have discrete impact on all species associated with either of those two habitats. The most obvious impact is that by converting a patch from one type to another, the species associated with the original type is expected to decline or abandon the patch completely, while the species associated with the new, converted type is expected to colonize it, as shown in Fig. 46. Note that the density values (number of individuals per ha) reflect the change in predicted population size, within a buffered

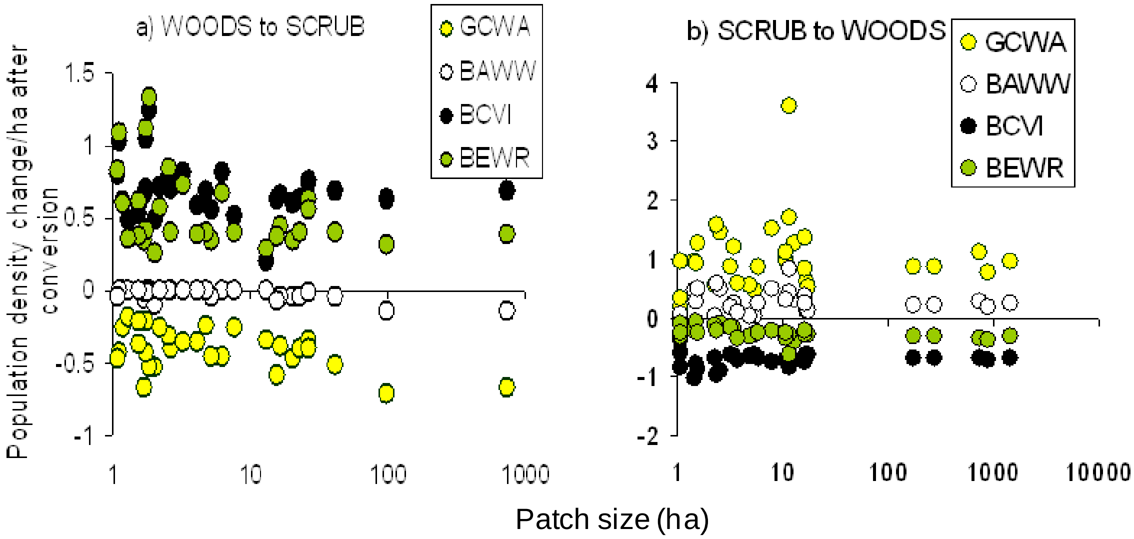


Figure 46. The relationship between patch size and the predicted density change under two conversion scenarios: WOODS to SCRUB (a) and SCRUB to WOODS (b). The total population change is predicted for the entire surrounding landscape, based on the size of the converted patch.

area around the focal patch, for each ha converted (reflecting patch size), thus the changes in population density predicted outside the target patch are based on how edge influences would be expected to change, which are themselves based on the type of patch converted.

What is not obvious from figure 46 is whether there are any patches in which the predicted declines of species initially present might be matched or exceeded by increases in other focal species, under a particular conversion scenario. Here, we considered only the responses of the two listed species of primary management concern. For instance, when considering scenarios where WOODS is converted to SCRUB, GCWA would be the declining species and BCVIs would be the increasing species. The opposite would be predicted where SCRUB is converted to WOODS. And because BCVIs appear to maintain a slightly lower density in their preferred habitat type, compared to GCWAs, it is unfair to look for a 1:1 exchange. Instead, we are interested in comparative differences. Ideally, we would seek patches where declines in one focal species would be mild and more than offset by gains for the incoming focal species.

To identify these preferred patches for management, we compared the predicted loss of declining species to predicted gains of increasing species for each of the 30 patches of WOODS (Fig. 47a) and SCRUB (47b). Again, these predictions show the predicted loss and gain of individuals throughout the landscape (in this case, results are not restricted to a particular target patch) relative to the amount of habitat converted. This means that we are considering influences throughout the landscape to actions taken at a particular location. To make the comparisons easier, we divided each panel into four quadrants based on the median value of population change for both decreasing and increasing species. This allows the identification of patches that are expected to have more or fewer losses or gains, compared to the median patch. Ideally, we would choose patches with fewer vacating individuals than average, but more colonizers than average (upper right-hand quadrant). Similarly, we might avoid patches where declines would be higher than usual, while increases would be lower (lower left-hand quadrant). The other two quadrants would, in general, represent more even trade-offs, where higher or lower rates of decrease may be offset by lower or higher (respectively) rates of increase. Of course,

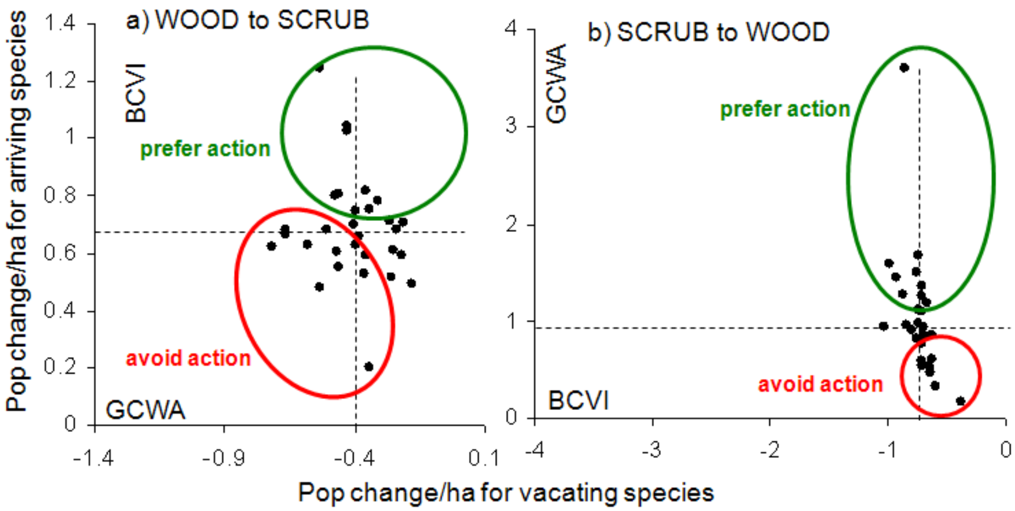


Figure 47. The trade-off between population changes for a vacating species compared to the arriving species under scenarios for conversion from WOOD to SCRUB (a) or SCRUB to WOOD (b). Panels are divided into quadrants through median values so patches where action should be preferred or avoided can be identified (see text for details).

considerable variability is manifest even within the quadrants and could guide management.

For example, in the SCRUB-to-WOODS scenario (Fig. 47b), there is far more variability in the predicted population sizes of incoming species (GCWA) than for vacating BCVIs (note lack of scatter along x-axis). In other words, the EAM predicts relatively equal declines for BCVIs in all 30 patches, whereas there is much more variability in the increases predicted for GCWAs (Fig. 47b). In such a case, managers might choose to target patches for conversion if they fall well above the median "increaser line" and avoid patches that fall below (Fig. 47b). Note that there is an outlier, where the incoming density of colonizers is much higher than for all other points. This is the same patch noted earlier, that showed a substantial change in Mean Dist to Edge (see yellow circle in Fig. 42). When examining the predicted effects of converting WOOD to SCRUB (Fig. 47a), variability is much more equally distributed, and patches with poor predicted outcomes (high decreaser values and low increaser values) are clearly indicated in the lower left-hand quadrant. Even here, we note that some patches show decreases in the predicted density of one focal species that are near the mean, while predictions for the increasing species are well above the median; these patches might be prioritized for habitat conversion since they would minimize undesirable effects on vacating GCWAs, while maximizing desirable effects on BCVIs, the expected colonizers in this case (Fig. 47a).

In completing this series of analyses, we have shown that simple metrics may be insufficient for capturing the relative conservation value of any particular patch. Specifically, traditional metrics like size and shape may not capture the value of the habitat sufficiently to identify the best patches for management action. In response, we have identified other metrics that can help managers make better judgments, even without considering species-specific responses. For example, if protecting larger areas of "interior" habitat is a goal, comparing Mean Distance to Edge, before and after modeling possible habitat conversion scenarios, is one way to identify the best patches for management action and does not require any species-specific data. Similarly, if avoiding effects that may be assumed from highly contrasting edges is the objective, one could target patches with a maximum proportion of edge with the most similar habitat type.

Finally, if the data are available, adding information about habitat quality relative to the focal species of interest can provide additional information about the conservation value of particular patches in the landscape. This can be especially important if management actions are planned for patches that are likely to have contrasting effects on different focal species. By considering both the "winners" and "losers" under management scenarios, we can seek to minimize losses while maximizing gains. In the increasingly common situations where managers face complex trade-offs, the EAM and the related edge effects toolbox can provide the insight needed to make better choices at the patch level, providing managers with clear predictions regarding the impacts of alternative management choices, as manifested at the landscape scale.

Step 6: Management Recommendations

Like Ft. Benning, these demonstration modeling exercises do not reflect current decision-making process on Ft. Hood. Currently, managers are allowing natural succession to increase GCWA habitat, and live fire exercises to create habitat for BCVIs. Nevertheless, it is likely that at some point management intervention will become necessary, and at that time the work presented here may be highly relevant. Until then, our results may be valuable in understanding potential tradeoffs in habitat management for the two focal species. Our results show that, in addition to having lower fecundity (Peak 2007), GCWAs also avoid edges. Further, our results strengthen the conclusions of a recent paper suggesting that scrub species, long associated with positive edge responses, in fact regularly avoid edges of their preferred habitat (Schlossberg and King 2008). We saw consistently that BCVI and BEWR avoided edges within their preferred habitat.

Of the species that showed the most consistent edge responses, all were habitat specialists and generally avoided edges of their preferred habitat. This means that relatively simple rules of thumb may suffice for managers on Ft. Hood to consider edges in their future management actions. For instance, larger more regularly-shaped patches would likely be preferable to smaller more complex shapes. Further, where possible, restoring or choosing patches near more similar habitat structure will likely result in better quality for these habitat-specific groups. Even where rule-of-thumb approaches may be useful, the EAM could be used to provide perspective and weight to these guidelines through greater quantification of species-level responses, and some issues arising from active approaches to landscape design and management may require finer quantitative measures. For instance, this project highlighted the ability of the EAM to identify specific areas of management action that may lead to better conservation outcomes. Similarly, there may be patches that should be preferentially identified as either GCWA or BCVI habitat because that would benefit the target species more than it would harm the competing species. In a situation where management actions designed to benefit one species necessarily come at the expense of another, this type of information could provide very helpful insight to augment simple management guidelines. This approach could be used to prioritize patches for management action or, alternatively, it could be coded directly into a map via a process such as the StopNGo mapping, introduced above.

As in other modeling efforts that compared alternative scenarios exercises, we found little difference between the replicates of each road scenario, suggesting that local patch differences integrate over the landscape in a way that tends to cancel out, as long as they are generated haphazardly. But the stark differences among patches in predicted habitat quality suggest that patches can be targeted in a way that might ameliorate or exacerbate the effects of various land uses and management actions. Finally, our work with the Malcolm model suggests that its implementation, using the simpler "IDEAL" approach, rather than the more labor-intensive "COMPLEX" approach may be sufficient for quantifying edge responses through the analysis of empirical data, and that its outputs can be used to parameterize the EAM.

.Side Collaboration: The Impact of Roads on Stress Hormones

Edges can have many impacts on organisms, including changing local densities, altering fecundity, or impacting physiology (Ries et al. 2004). We had the opportunity to collaborate on a project headed by Tim Hayden (ERDC-CERL) that measures physiological responses to military activity on birds (SI-1396). Working specifically with Luke Butler, we used the road map we had created (Fig. 4b) to targeted 50 sample points within GCWA habitat, ranging from zero roads and trails (within 150m of the sample point) to areas highly impacted by roads or trails (Fig. 48a). Dr. Butler captured 49 GCWAs and 48 white-eyed vireos (WEVI) at targeted points and measured their glucocorticoid corticosterone (CORT) levels. Results indicate that GCWA CORT levels fell at higher road densities (Fig. 48b), indicating elevated baseline stress, but no effect was seen on the less habitat-sensitive WEVI (Fig. 48c). Interestingly, stress does not seem to be associated with increased activity level along roads, or with inter-specific interactions. Dr. Butler hypothesizes that increased snake densities along roads may be contributing to increased stress. These types of studies are important because they demonstrate the multiple ways that edges can impact populations and also highlight how edge effects can cascade through different trophic levels of the ecological community.

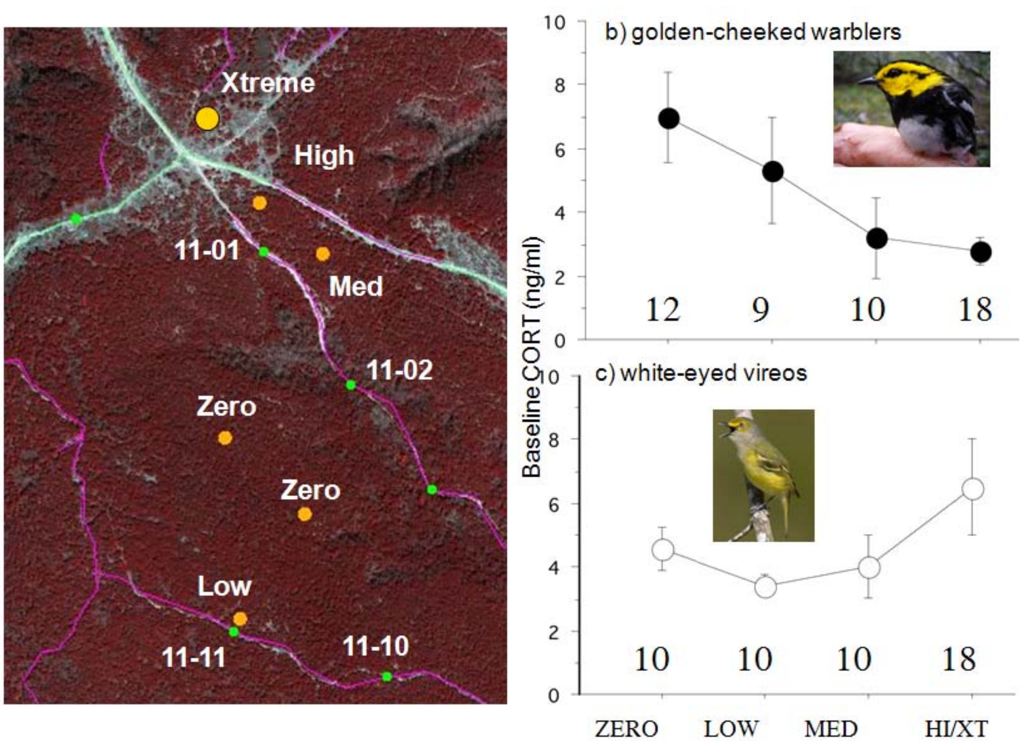


Figure 48. In collaboration with Luke Butler of Tufts University (from SI-1396) we targeted 50 sample sites to collect blood samples to test stress hormones (CORT) in GCWA (b) and white-eyed vireos (c) based on road density.

6. Conclusions and Implications for Future Research

This project advanced understanding of landscape context and edge effects by providing a powerful framework for the quantifying and modeling species-level impacts of landscape-scale changes resulting from different management actions. Further, it provides an enhanced set of tools for analyzing the potential impacts of edges on multiple species, while helping to shift focus from single-species management to a larger community of organisms. Collectively, the results presented in this report, combined with other recent developments in landscape ecology and the study of edge effects, indicate that we are rapidly expanding our predictive capacity regarding this previously confounding set of issues. Further, improved understanding and advances in modeling approaches, including those presented here, are likely to enhance our ability to design managed landscapes for improved conservation outcomes.

Our project had two major goals: 1) to develop tools for considering edges in landscape design and management, and 2) to develop and demonstrate these tools at two military installations. We were successful on both counts and met all the major goals outlined in our original proposal, while making progress in new areas as well. In doing so, we continue to develop our understanding of edge ecology and offer managers and scientists a way to work together to understand how edges and the differential response of species to these edges could impact their own broad-scale decisions and management activities. We made several advances in the study of edge effects, developing a practical approach for modeling edge effects based on field data and performing multiple landscape-scale modeling exercises that demonstrated the impact of scaling up local species-specific edge responses to the landscape level. Further, we developed a suite of practical tools that will be valuable to researchers and conservation managers interested in landscape-scale patterns in species abundance. The cornerstone of this toolkit is the EAM – the only tool that can take realistic edge responses for multiple edge types and integrate effects while extrapolating over entire landscapes. Further, we have developed two R-packages that can aid researchers in modeling edge effects. One package, “edgefx” offers the first practical implementation of an advanced model (Malcolm 1994) that captures complex patch geometry when measuring edge effects. Another package takes the voluminous EAM output and processes it, producing preliminary graphs useful in visualizing the major trends from landscape-scale models. These approaches and tools are described on a new website, the Edge Effects Resource Center (http://www.clfs.umd.edu/lries/EERC/EERC.html).

Our work here adds to the rapidly expanding scholarship on edge effects that has had a real impact on the ecological and conservation communities, placing edge responses in a predictive, practical framework. The first advance comes through our work examining the implications of scaling fine grain edge effects to the landscape. Through the modeling of multiple management scenarios on both Ft. Benning and Ft. Hood, we have done the most extensive evaluation to date of the likely impacts of landscape structure in patterns of species' abundances. We had two main results from this phase of our work. The first is that, when integrated over landscapes, multiple different scenarios were predicted to have similar outcomes when the overall area under active management action (i.e., amount of habitat affected) was held constant. This was largely consistent throughout our different analyses, suggesting that when multiple management actions are randomly implemented over large areas, local differences in habitat configuration, some exacerbating and others ameliorating impacts, tend to balance out. However, our work also consistently showed that patch context and shape can have a profound impact on the predicted response at particular sites. That means that when managers are planning management actions, the outcome of their choices can be strongly affected by a few influential changes in landscape structure. By incorporating information from the EAM, managers have the opportunity to anticipate and influence overall outcomes by identifying the relatively few locations where changes in management are likely to have disproportional effects. We show this through a new approach to incorporating the output from the EAM (as well as other information) into management decision making, an approach that we call "StopNGo" mapping. This mapping codes information into a manager's current landscape map about whether the impacts on patches exposed to management actions might be exacerbated or ameliorated, due to the influence of the surrounding habitats, manifest as edge effects. We were able to show that choosing sites for action using this information could increase predicted population levels for multiple species. We hope to pursue this avenue of research further, because we believe that it has the potential to bring together multiple threads of information about the landscape and present them in a straightforward and useful manner.

Our research on the "scaling-up" of edge effects has also shown that small-scale effects integrate up to the landscape in ways that are often surprising. For instance, in some cases where we would expect strong divergences in the predictions of the EAM and NULL, differences in modeled outcomes were negligible (e.g., Fig. 34). In cases where the magnitude of edge effects was variable, we were surprised that the distance to which the edge response extended into adjoining habitats had minimal effects on predicted density. However, simply changing the symmetry of the edge response across the edge (i.e., shifting the response completely into one habitat or another while keeping its shape constant) had the largest overall impact on landscape-scale distributions (Fig. 27). Thus, factors that influence exactly where edge-sensitive species reach maximum or minimum abundance are of interest, and should be the focus of future study. Our results also identify cases where simple metrics may suffice for understanding responses to landscape-scale changes in context and structure, as well as when more complex metrics become necessary. In fact, our research suggests that simple metrics, such as distance to the closest edge, may often be sufficient for the most habitat-sensitive species, as long as the species is known to always avoid edges within their preferred habitat(s). In these cases, simple rules, such as directing attention to larger, more regularly shaped patches, may work well. In most cases, if those patches are surrounded by habitat with similar structure, this focus is likely to provide an additional benefit with little downside. However, such generalizations are unlikely to apply to multi-species planning efforts. When focusing on a larger segment of the biotic community, species with more variable edge responses are common, and our work suggests that simple metrics are insufficient for understanding complex edge responses (Table 5), and in such cases, output that is currently available only from the EAM is likely to prove necessary for understanding the dynamics of multiple species and predicting their responses.

Our findings are of more than passing interest, because these and other efforts (e.g., Fletcher et al. 2007), suggest that many of the patterns associated with fragmented habitats emerge from the scaling-up of local edge effects. For instance, we found that response thresholds, where patterns level off after a certain distance from the edge, were common though not ubiquitous. In addition, we found that a distinct pattern in the variability of responses across fragmentation gradients emerged, which has also been noted in the literature. Finally, edge effects are predicted to lessen differences in the quality of adjacent habitat types that should be distinct, based on basic habitat preferences alone. Where edge responses are strongest, mean differences in density between habitats of very different quality can almost completely erode (Fig. 28). This work suggests that large site-to-site variability in edge responses, widely noted in the literature, may in part be explained by differences in patch structure and context. However, other factors, such as connectivity and local patch quality, may also be important. Determining how edge and context interact with these other major drivers of local habitat quality should be a focus of future research.

Another advance allows the incorporation of complex patch geometry, typically encountered in real landscapes, into edge effects models. Traditional approaches for measuring edge responses assume that edges are straight and free of the influence of any other surrounding edges (Fig. 10a), yet real landscapes never meet those assumptions (Fig. 10b,c). We were forced to confront this assumption because of our central goal of extrapolating edge responses over entire landscapes via the EAM. In doing so, we discovered that the assumption of “ideal” edges has potential implications both in measuring edge responses and in extrapolating them to the landscape scale. Our work applying Malcolm’s 1994 model of complex edge geometry allowed us to develop a tractable approach to implementation on any landscape. These tools are useful in measuring edge responses in the field and lead naturally to results that can be used to parameterize the EAM. We also performed the first test of the model on multiple patch configurations and found that the model has important implications for landscape-scale patterns in species abundance. Our work on this topic has exposed a major weakness in the edge literature. Despite the fact that real landscapes commonly have three or more habitats converging at a particular location, there are no empirical studies of how multiple edges interact to affect habitat quality the abundance or distribution of organisms. To address this shortcoming, we have begun a new field effort to collect the first data on this topic. We intend these data to form the basis for developing the mathematical models required for integrating multiple edge effects, and ultimately we plan to extend the EAM to incorporate these effects, which are common in virtually all landscapes.

A Vision for the Continuing Evolution of the EAM

Through the process of developing this next generation of EAM products, we have continued to refine our vision of the most useful modeling and analytical approaches and how we might combine them in the most user-friendly environment. One of the primary challenges we grappled with is the increasingly complex and varied structure of each user’s individual computer system and the current reliance on proprietary desktop software. Extremely diverse user configurations and the multiple versions of ESRI's ArcGIS Desktop platform make EAM configurations difficult to manage and maintain going forward. We have therefore been exploring the possibility of developing the EAM within a web-based, on-line environment as a next logical step in model and platform development. This would have many benefits for our intended user community. First, the user would not be required to have purchased an expensive license in order to use the tool. A web-based EAM would require no installed ArcGIS software, only a secure broad-band internet connection and web browser. Second, we would not have to contend with a quick succession of new software releases that can render our computer code obsolete in a matter of a few years. All software upgrades would take place on the hosted server only, and would be completely transparent to the end-user community. Additionally, we would not have to contend with the quirks of each user’s computer environment (a constant consideration with ArcGIS), although we would have to ensure that our software was compatible with all common desktop browsers. Finally, since the user would not need to download any software, maintaining a secure architecture would satisfy an increasingly security-conscious military and government computing environment. We are still determining whether the available open-source GIS software has reached a level capable of supporting a free-standing, web-based EAM. Even if not, the natural progression of the open-source movement ensures that it will shortly. Until we are able to pursue this avenue, the revised and improved version described here will provide comprehensive functionality for any user with access to ESRI's ArcGIS 9.2 or 9.3 and the spatial analyst extension.

Another major benefit of the web-based approach is the possibility of launching an on-line database of edge response functions. This database could initially be culled from the literature and from collaborating researchers, providing a valuable resource to managers and scientists. Although this is an effort that we could undertake prior to launching a web-based EAM, the benefits of tying this type of tool with an on-line, data-rich environment is that it would allow and encourage any EAM user to post the edge responses developed for their focal species and landscapes into an on-line database. This database would act as a resource for other users developing their own edge response functions and also as a potential source of data for further scientific inquiry. For example, it could be a critical aid in research efforts attempting to determine the circumstances under which species are most or least sensitive to habitat edges, a framework important for developing responses when field data are lacking (see section 5.3). We view this as a natural progression for an avenue of research that has seen consistent progress over the past decade, resulting in a continually growing data base of edge responses that could be centralized and made publically available. There is increasing pressure to manage for multiple goals, even as the case for formal conservation planning is questioned (Meier et al. 2004). To meet this challenge, we plan to continue the development of a suite of modeling and analytical tools, and to offer them in an integrated, practical toolbox for considering some of the most critical effects of habitat fragmentation – edge effects – to the research and management communities.

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List of Appendices

Appendix A: List of Scientific/Technical Publications

1. Articles in peer-reviewed journals

Ries, L. and T.D. Sisk. *In press*. What is an ‘edge species’? The implications of sensitivity to habitat edges. *Oikos*

Ries, L. and T.D. Sisk. 2008. Edge effects are predicted by a simple model in a complex landscape. *Oecologia* **156**:75-86.

Fletcher, R.J., L. Ries, J. Battin, and A.D. Chalfoun. 2007. The role of habitat area and edge in fragmented landscapes: definitively distinct or inevitably intertwined? *Canadian Journal of Zoology* **85**:1017-1030.

Lindemayer, D, and 26 Coauthors, incl. T. Sisk. 2007. A checklist for ecological management of landscapes for conservation. *Ecology Letters* **10**:1-14

4. Conference or symposium abstracts

Butler, L.K., L. Ries, T.J. Hayden, I.A. Bisson, M. Wikelski, and L.M. Romero. 2009. Physiological and demographic effects of roads on an endangered, old-growth specialist and a common generalist. *Integrative and Comparative Biology* **49**:E24-E24

5. Text books or book chapters

Hannon, L. L. Ries & K. S. Williams. 2009. Invertebrates of the San Pedro River. Invited book chapter *in* (J. Stromberg & B. Tellman, eds.) Conservation of the San Pedro River, Island Press.

Sisk, T. D. 2007. Incorporating edge effects into landscape design *In* (D. Lindenmayer and R. Hobbs, eds) Managing and designing landscapes for conservation: moving from perspectives to principles.. Blackwell Publishing, Ltd. Oxford. 587 pp.

<u>Manuscripts in preparation:</u>

Sisk, T. D. and L. Ries. The use of the Effective Area Model in Conservation and Management. To be submitted to Conservation Biology in Practice

Ries, L, J. Greenberg, and T. D. Sisk. Emergent properties of fragmentation when edge effects are extrapolated over landscapes. To be submitted to Ecography

Ries, L. and T. D. Sisk. Balancing trade-offs for two endangered species with conflicting needs: the use of landscape context to maximize benefits. To be submitted to Landscape Ecology

Ries, L. and E. Goldberg. Measuring complex and multiple edge effects in real landscapes. To be submitted to Ecological Applications

Appendix B: The Effective Area Model User's Guide

Note: the actual EAM user's guide is an on-line guide developed in .chm format and available both free-standing and as an embedded help manual within the EAM program, but for the purposes of this report we converted it into Word (.doc) format.

Effective Area Model (EAM) 2.0 (beta) – For use in ArcGIS 9.2 and 9.3

Original Concept: Thomas D. Sisk[1] (http://www.cefns.nau.edu/Academic/EnvSci/Lab/)
Development and Design: Leslie Ries[2] (http://www.clfs.umd.edu/lries/)
Programmer: Jared Andre, IronRim LLC (www.ironrim.com)

This program is an update of an earlier version of the EAM, developed for ArcView 3.2 in Avenue by Haydee Hampton[1].

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QUICK START GUIDE

If you don't like reading the full explanation or if you've used the EAM and just need a quick reminder – this quick guide is for you. Each step is described briefly, but linked to the full explanation in the guide.

WARNING: WE RECOMMEND STARTING EACH RUN WITH A NEW, EMPTY ARCMAP WINDOW.   THEN, LOAD ONLY THE MAP YOU PLAN TO MODEL.

<u>Step 1: Launch the EAM</u>

<u>Step 2: Start Run</u>

Name the run and save output if desired (click Next)

<u>Step 3: Input Habitat Data</u>

Select the map to run through the EAM (click Next)

-Ideally, there will only be one map to select – see warning above

<u>Step 4: Select Habitat Field</u>

Select the field that contains your habitat attributes

<u>Step 5: List Habitat Types</u>

Select the habitat types you wish to model and choose your grid size
(Click Next)

-This list is built from the fields in your habitat map's attribute table

-Only one option is available for grid input (which only allows one attribute)

AFTER THIS STEP, THE EAM RASTERIZES YOUR HABITAT MAP, FINDS ALL THE UNIQUE EDGES AND DISTANCES, THEN LOADS A SERIES OF GRIDS INCLUDING HABITAT AND EDGE TYPE INTO ARCMAP, YOU ARE THEN REQUIRED TO ENTER SPECIES INFORMATION TO APPLY THE EAM.

<u>Step 6: Enter Edge Data</u>

-Enter edge response functions either manually into the dialog or import

<u>Step 7: Click "Run the EAM</u>

DURING THIS STEP, THE EAM APPLIES THE EDGE RESPONSE FUNCTIONS TO THE MAP YOU ENTERED, AND GENERATES A SERIES OF DENSITY GRIDS SHOWING PREDICTED DENSITY THROUGHOUT THE LANDSCAPE, YOU CAN NOW SUMMARIZE THOSE GRIDS OR EXPORT THEM FOR USE ELSEWHERE

<u>Step 8: Density Grid Summary</u>

-Summarize both species density grids and habitat grids based on any attribute

INTRODUCTION

Effective Area Model Overview

The Effective Area Model (EAM) is a habitat model that weights habitat quality by the proximity and type of edge. Edges are a key component underlying how fragmentation influences the abundance and distribution of organisms. Fragmentation effects can generally be broken into three separate (yet inter-related) dynamics: edge, area and isolation effects. A substantial empirical body of work has been built over the past several decades documenting the influence of all three on the distribution and vital rates of a whole suite of organisms (as well as non-organic dynamics such as micro-climate and fire). However, the practical tools developed to model organismal responses to fragmentation have largely focused on patch size and isolation. Edge effects are usually ignored or dealt with by focusing exclusively on patch interiors. We believe that these approaches omit a great deal of information about habitat quality throughout most landscapes. Indeed, in some increasingly fragmented landscapes, almost all remaining habitat patches are effectively “edge”. We have developed this model to fill this gap in the suite of available landscape models.

The Effective Area Model takes known or hypothetical edge density responses and extrapolates them to entire landscapes, then integrates densities in user-specified landscape units (i.e., patches, distinct habitat types or landscape regions) to predict local population sizes. The Effective Area Model takes its name from the concept that different patches of the same size and type may be able to support larger or smaller populations dependent on their shape or context. Since edge effects tend to modify habitat quality (either positively or negatively depending on the organism and edge type), larger or smaller population sizes may be expected in different patches of the same size, thus influencing the “effective area” of each patch. This model allows users to incorporate the most up-to-date science on the influence of edges on habitat quality and patch capacity and therefore to predict the impacts of modifying landscape structure or taking various conservation actions.

The Effective Area Model is implemented within an ArcGIS platform (for versions 9.2 and 9.3). The model requires two types of data: 1) habitat maps formatted as polygon layers (shape file or feature class) or grids and 2) edge response functions for each species of interest. The model extrapolates predicted densities over entire landscapes and then offers the user several ways to summarize the resulting density grids.

Suggested reading:

Sisk TD, Haddad NM, Ehrlich PR (1997) Bird assemblages in patchy woodlands: modeling the effects of edge and matrix habitats. Ecol Appl 7:1170-1180

Ries L, Fletcher RJ, Battin J, Sisk TD (2004) The ecology of habitat edges: mechanisms, models and variability explained. Ann Rev of Ecol Evol and Syst 35:491-522

Brand LA, Noon BR, Sisk TD (2006) Predicting abundance of desert riparian birds: validation and calibration of the Effective Area Model. Ecol Appl 16:1090-1102

Battin, J and TD Sisk. 2003. Assessing landscape-level influences of forest restoration on animal populations. In *P. Frierderici and W.W. Covington, editors. Ecological restoration of southwestern ponderosa pine forests. Island Press, Covelo, CA.*

<u>Instructions for Beta Testers</u>

This is the first beta release of the EAM for the 9.2 and 9.3 versions of ArcGIS. This release is intended for error-checking and eliciting comments for improving or clarifying the use of the model or the Help File. We assume that users are familiar with ArcGIS. Please send your questions, comments, and findings of errors or bugs to Leslie Ries (lries@umd.edu). Please let us know what version of ArcGIS you use, your operating system, and the types of data layers used. We may ask you to share your habitat layers and response functions so that we can attempt to duplicate errors or problems. We welcome all suggestions about how the model's interface, operation, and help files could be improved. Thank you for taking the time to work with an early version of this model.

NOTE TO GRID USERS: The majority of testing on this product has been with polygon files, and we recommend converting grids to polygons (see <u>A Note About Grids</u>). But please let us know if you have any problems implementing the EAM on grid data.

<u>Edge Effects Resource Center</u>

We are gathering all of our resources related to edge effects in a central web location, the Edge Effects Resource Center (<u>http://www.clfs.umd.edu/lries/EERC/EERC.html</u>).

Please continue to check that site for useful resources and updates to the EAM.

<u>System Requirements</u>

This program runs on ArcGIS 9.2 or 9.3 (ArcView level) and the spatial analyst extension must be installed and activated.

The Microsoft.NET framework must also be installed as part of the operating system. Vista and Windows7 automatically includes this, but if running Windows XP (and if updates aren't current), you will be prompted to download this free software.

In general, ArcGIS runs better when there are 2GB (better 3GB) of available RAM, this is not related to the running of the EAM.

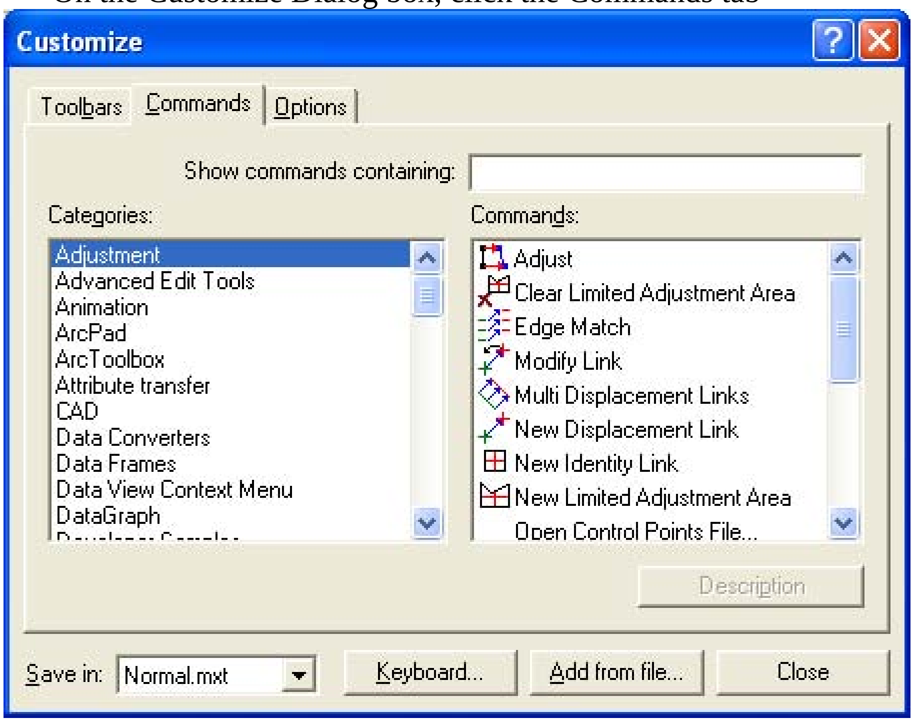
This program runs most efficiently when a new, empty ArcMap window is loaded ONLY with the map to be modeled.

Installation Instructions

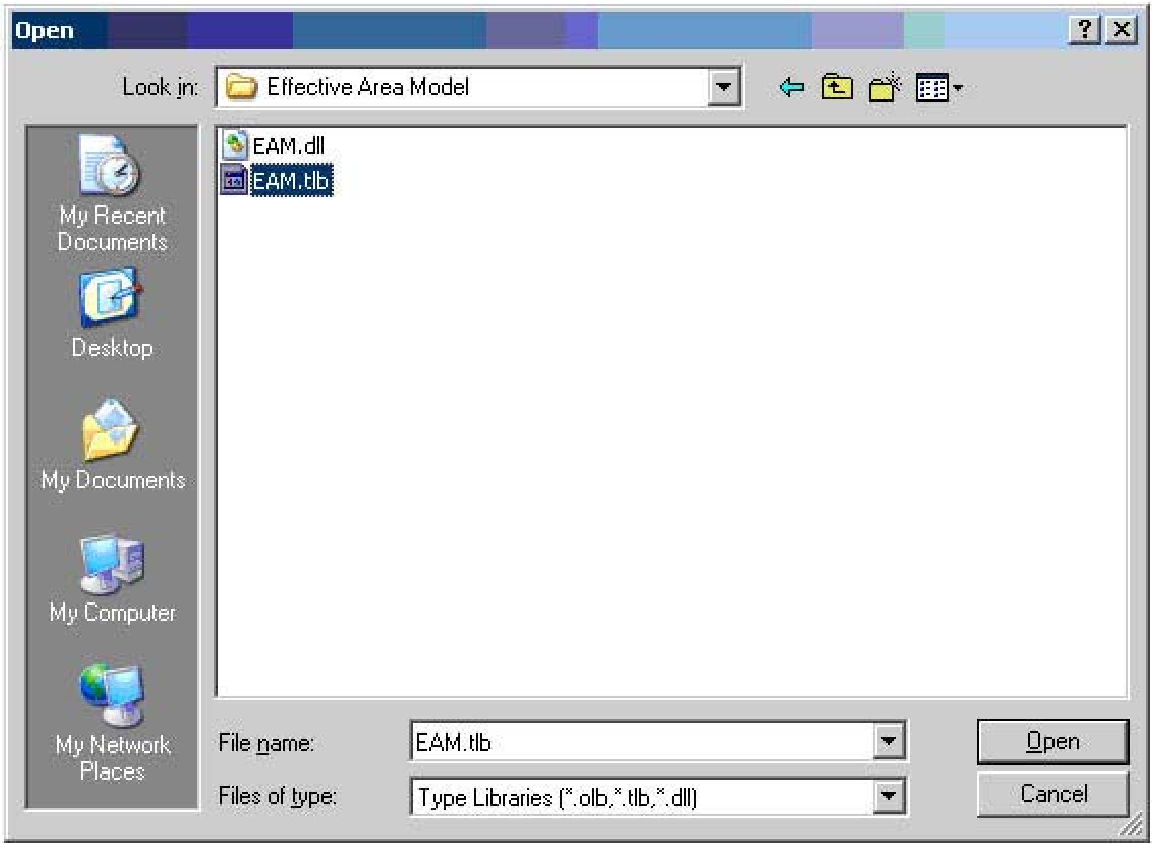
The EAM extension will install into ArcGIS as a button on the ArcMap menu bar.

Steps to install:

- Unzip the EAM2.0beta.zip and run the Setup.exe.
- If the Microsoft.Net framework is not loaded on your computer, you will be prompted to load it.
- You will be unable to install the EAM if you do not have Spatial Analyst installed and activated in ArcMap.
- Follow the directions on the Setup Wizard (basically, clicking “Next” on each screen). The user may change the installation folder if desired.
- When the Installer is finished, you should launch ArcMap to embed the button that launches the EAM on an ArcMap toolbar.
- Click Tools > Customize… to launch the Customize Dialog box
- On the Customize Dialog box, click the Commands tab

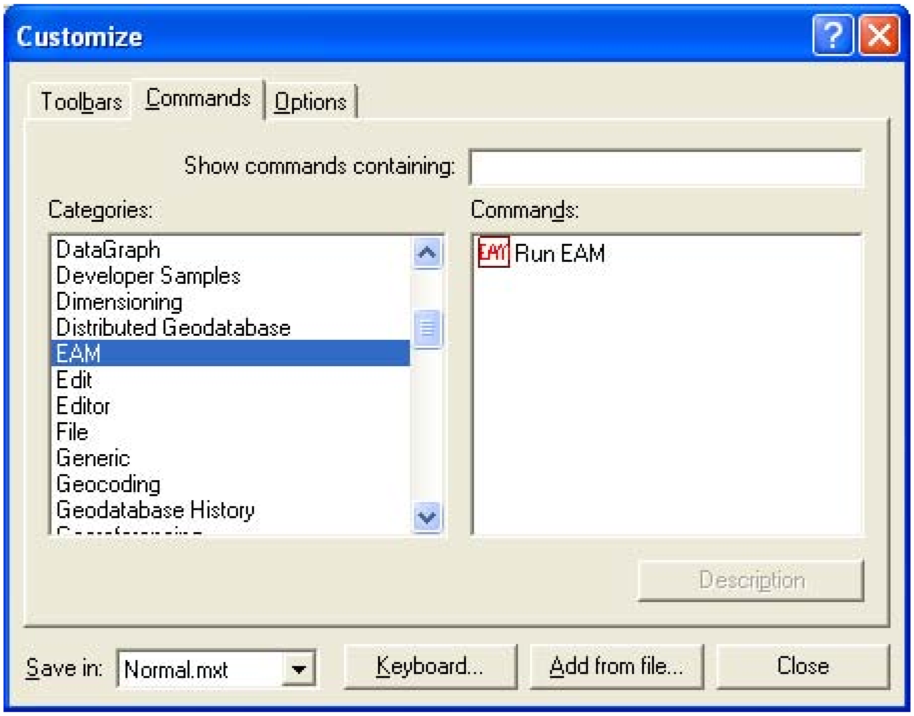


- Click Add from file…
- Navigate to the location where you installed the EAM and find the EAM.tlb file,



- Click Open
- You should get a message that new objects were added

- Click OK
- With the Customize Dialog Box still open, navigate to the new EAM category and click and drag the “Run EAM” command onto a toolbar in ArcMap.



- Once the new command is on a toolbar, close the Customize Dialog Box.
- THE EAM IS NOW INSTALLED!!!
- To run the EAM wizard, click the EAM Button
- Note that if you end up uninstalling and reinstalling a new version of the EAM, you only need to run the installer – you do not need to go through the steps to add the EAM button to your toolbar – it will already be there.

To uninstall the EAM, launch your Control Panel, go to Add/Remove programs – and remove (uninstall) the EAM.

To reinstall – just run the Installer (you won't have to reinstall the button as above).

DATA REQUIREMENTS

The EAM requires two types of data: a habitat layer and edge response parameters. The habitat layer can be a polygon file or grid, but we recommend using polygon files (see "A Note About Grids"). Information on edge responses will be required for each species being modeled at each unique edge type within modeled habitat classes. The user must provide both the habitat layers and the edge response functions.

Habitat Layers

Habitat layers can be polygon or grid files. Habitat layers should be projected with map units of meters. If a grid, each grid value must be linked to a habitat class. If a polygon, the habitat layer must have at least one attribute field that specifies the habitat class of each polygon. Further, polygon layers should be as "clean" as possible, meaning that there aren't gaps and slivers between polygons and that individual polygons do not overlap. If slivers and gaps are present, we recommend setting the grid size for EAM processing to a size generally larger than the slivers and gaps. If the user is interested in patch-based statistics, then the polygon layer should be dissolved on the habitat field of interest. In general, dissolving on the habitat field is good practice (although doesn't make sense in all situations). The habitat field can be called anything and have as few or many habitat classes as the user feels is appropriate for their study system. Habitat descriptions should be short (i.e., FOREST) rather than overly descriptive (i.e., GENERAL FOREST WITH PINE AND HARDWOOD). The main challenge in developing habitat maps is determining the optimal number of habitat classes within the habitat layer. There should be a sufficient number of distinct habitat classes to capture how focal organisms respond to the major vegetation classes present on the landscape. For instance, if focal organisms are only found in old-growth pine, then forest ideally should be stratified by age and type – however for some forest generalists, it may be enough to classify habitat as either forest or non-forest.

The goal of capturing the responses to fine differences between habitat classes needs to be balanced by the fact that the greater the number of specified habitat classes, the greater the number of resulting edge types. All landscape responses within the EAM are specified through edge response functions (see below), so the number of parameters that need to be entered is driven by the number of edge types. The user is cautioned that the maximum possible number of edges in a landscape is $n*(n-1)$, where n is the number of habitat classes. So, if you have specified five habitat classes (i.e., FOREST, SHRUB, MEADOW, URBAN, WATER), then there will be up to 5*4=20 unique edge types. That there are 20 unique edge types results from the possibility that each habitat class borders the other four within the landscape (for instance, FOREST could be bordered by any of the other four types: SHRUB, MEADOW, URBAN, WATER).

Of course, the user may not be interested in responses within all five habitat classes. In the above example, if the focal organism is terrestrial, it makes no sense to model their response in WATER. Further, if only associated with natural habitat, responses in URBAN cover can also be eliminated. Indeed, if the organism being modeled is largely restricted to FOREST, it may only make sense to model their response within FOREST habitat (although it may be necessary to stratify into multiple forest types). However, the model will still require information on how the focal species (in this example) responds to all FOREST edge types. That means that their response, within FOREST, to SHRUB, MEADOW, URBAN, and WATER edges – need to be specified. If the organism responds similarly to FOREST|MEADOW and FOREST|URBAN edges, it may then make sense to combine those two habitats (MEADOW and URBAN) into a single class (OPEN). Minimizing the resulting number of edge types, while still capturing the important habitat responses of each model organisms is a key challenge of using the EAM. There are two ways of reducing the number of edge types: 1) reduce the number of overall habitat classes in the habitat layer and/or 2) only model responses within a subset of habitat classes.

Users may be interested in modeling habitat and edge responses on a single landscape, on multiple versions of the same landscape, or on multiple landscapes. For instance, the user may be deciding between several management options, and a map layer could be developed for each of those options. The EAM could be run on each and the resulting population projections compared for one or several species. We refer to this process as alternative scenario modeling. The details of scenario modeling will be different for each study system and each management challenge, but we offer some guidelines to implementing an alternative scenarios approach on our Edge Effects Resource Center website.

A Note About Grids

We recommend running the EAM on polygon shape files. There are two reasons: 1) raster data can be "noisy" and any single pixels will cause edges within habitat regions, 2) there is less flexibility to summarize the data grids since raster grids can not carry associated habitat information. Further, we have done little testing on the EAM using grid data – so if you encounter any problems, please let us know (lries@umd.edu).

If working with grids, we recommend converting raster data into polygons. In doing so, we also recommend that you "clean" the files so that you do not allow pixilated habitat to become small polygons. The functionality you'll need is on the Spatial Analyst toolbar within ArcGIS. The Neighborhood tools will allow you to clean the files and the Raster to Feature tool will convert your data (see ArcGIS help manual for details).

Edge Response Functions

The EAM requires parameters on edge responses for each species at each unique edge type on the landscape *but only within classes specified as focal types*. After specifying the attribute field that contains the habitat classes, and which specific habitat classes you wish to model (specific instructions to do this are in the following section on running the EAM), the EAM will generate a list of each unique edge type on the landscape for which parameter values are required. The user is required to enter four parameters for each of these unique edge types:

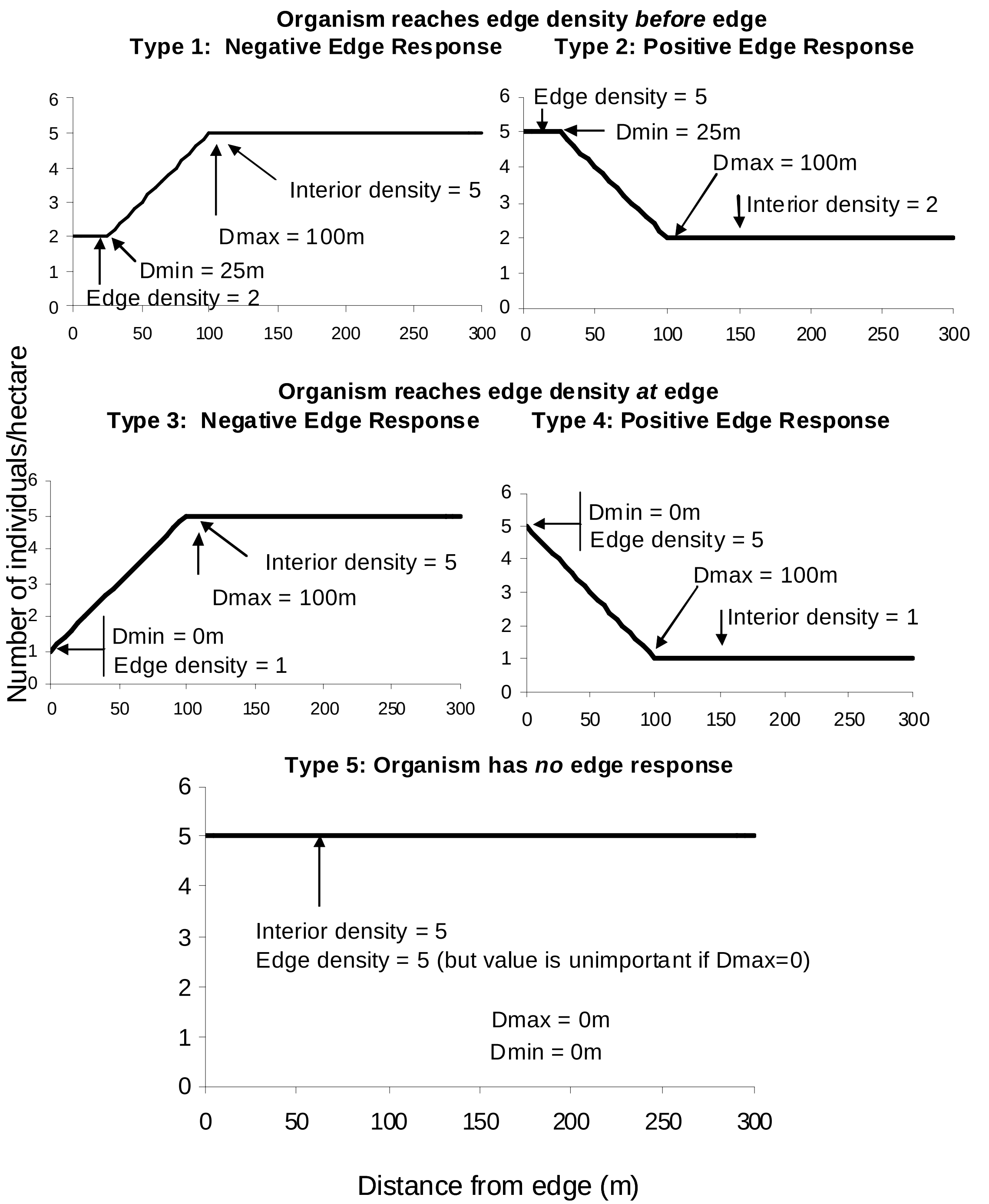
Interior_Density: This is the number of individuals per hectare that is found in the interior of the habitat (beyond the regions of edge influence, specified with **Dmax**). If there are multiple edge types for the same habitat class (i.e., FOREST|MEADOW, FOREST|URBAN, FOREST|WATER), then logically the interior density should be the same for all edge types within the same habitat class. However, the EAM currently does not impose this restriction.

Edge_Density: This is the number of individuals per hectare that is found at the edge. This can be different for every edge type, even within the same focal habitat. Organisms may reach their edge density at the edge, or there may be a region of some width (specified with **Dmin**) that they maintain the same edge density.

Dmax: This specifies the distance into the habitat that all edge effects extend. **Dmax** can be different for each unique edge type. If **Dmax** is set to 0, then the model assumes no edge effects regardless of the values entered in **Edge_Density** or **Dmin**.

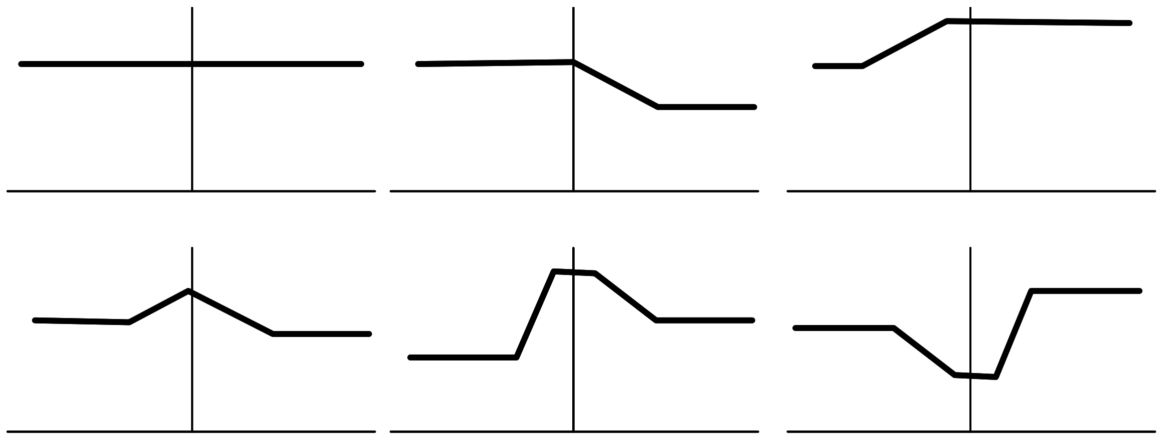
Dmin: This specifies the width at the edge zone over which the **Edge_Density** extends. For instance, if a species is never found within 100m of an edge, than the **Edge_Density** is 0 and **Dmin** is 100m.

There are five basic types of edge responses that can be modeled using these parameters and these are shown below. Edge responses can be either positive (densities increase near the edge) or negative (densities decrease near the edge). In all five types, a flat density function is assumed past Dmax. In the first two types, the organism reaches their edge density within the habitat (so not at the edge), and there is a zone where the edge density remains constant (set by Dmin). These edge responses can be either negative (Type 1) or positive (Type 2). In the second two types, the organism reaches their edge density at the edge (so Dmin = 0). These edge responses also can be either negative (Type 3) or positive (Type 4). Finally, organisms may show no edge response to some or all edge types (Type 5).



Although only the above five types of edge responses are possible using the four parameters in the model (Edge_Density, Interior_Density, Dmax, Dmin), the fact that edge responses are modeled separately on each side of the edge means a multitude of different edge responses are possible when considered over the entire edge gradient (from the interior of one habitat into the interior of the other). This method allows for great flexibility in specifying edge responses without the need for non-linear equations.

Below, we show some examples of edge responses that are possible using these four parameters.



and many more…

During EAM processing, the functions are called based on the type and distance to the closest edge for each pixel on the landscape (in a grid that is generated by the program). If the distance is less than **Dmin**, the edge density value is recorded for that pixel. If the distance is greater than **Dmax**, the interior density value is recorded. If the distance is between **Dmin** and **Dmax**, a linear function is used to determine the value. At this time, only the distance to closest edge is used to weight habitat quality in this version of the EAM. However, we are developing algorithms that can integrate the influence of all edges within **Dmax**. Currently, we have developed this capability on binary maps (for research purposes only) within an R-package called “edgefx”. Please see the Edge Effects Resource Center for more information.

Techniques to develop edge responses vary depending on the data you have available. We give guidelines at our Edge Effects Resource Center.

Running the EAM

Step 1: Launch the EAM

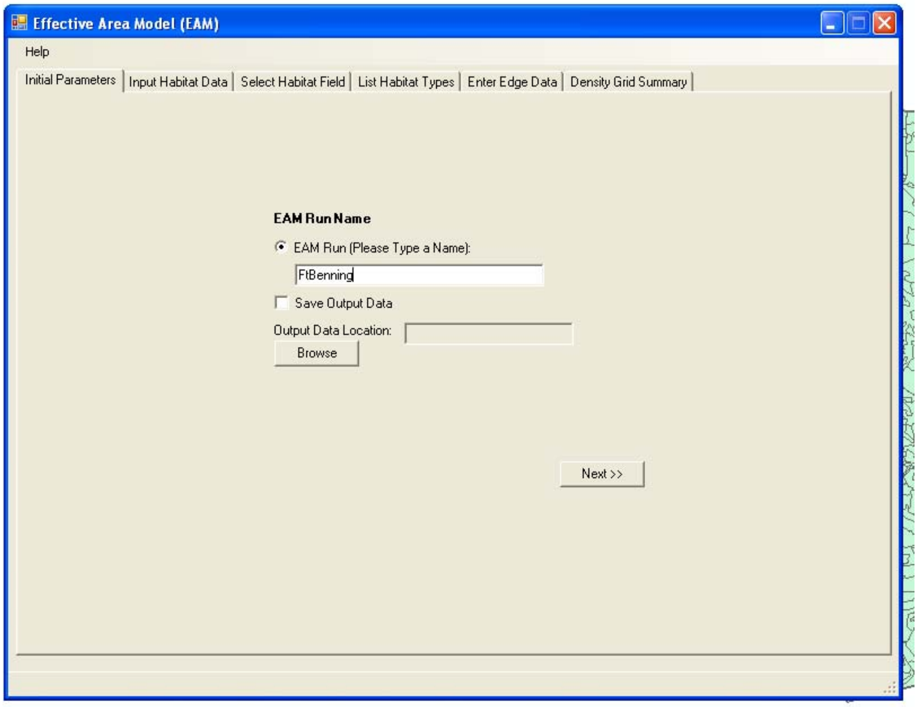
To launch the EAM, click the EAM button on the toolbar. Make sure that the habitat layer that you are going to use is loaded into ArcMap. We recommend that the only map you have loaded in ArcMAP is the one you are going to run through the EAM.

The dialog box that contains all the EAM functions is arranged in a series of steps that is organized into multiple tabs. To back up at any point in the process, click back to an earlier tab. But to progress forward through the tabs, always use the “Next” button.

Step 2: Start Run

To begin an EAM run, type a name for that run (i.e., Test1 or Run1). The name you type will be saved and appear in any summary tables that are generated later in the process.

If you would like to save the output of this run, check "Save Output Data" and type or browse to a folder location. The output will all be saved in that folder, along with a map file with the name of the run you chose above (i.e., Run1.mxd).



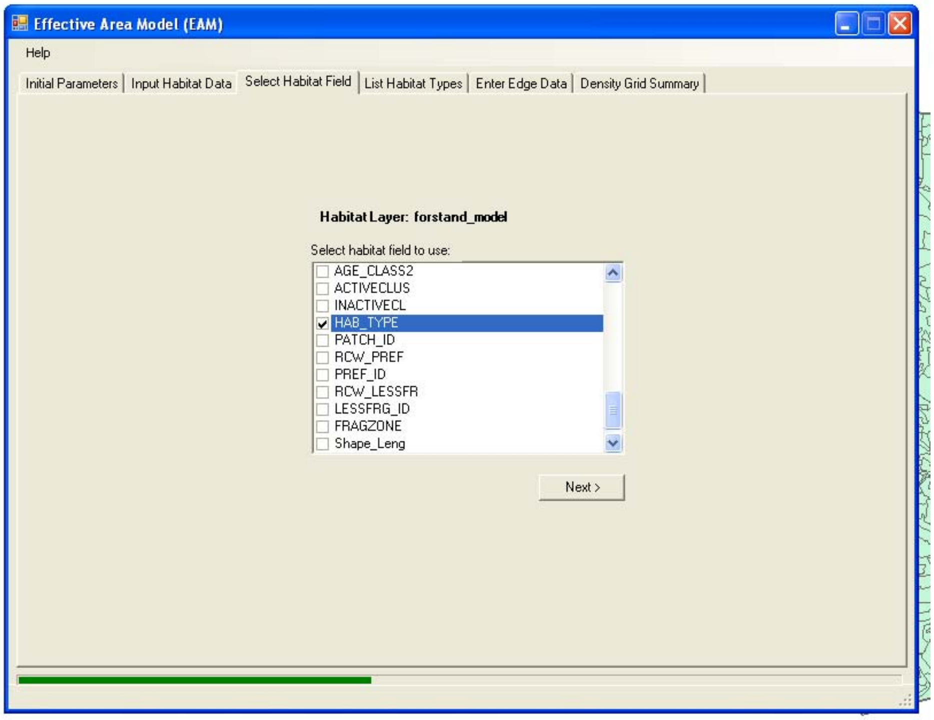
Click "Next" to get to the next tab (Input Habitat Data).

Step 3: Input Habitat Data

Here, you simply choose the habitat layer via a drop down menu. Click "Next" to get to the next tab (Select Habitat Field)

Step 4: Select Habitat Field

After choosing the habitat layer to be modeled, the EAM builds a list of all the fields in the habitat layer's associated attribute table. The user should check the field that contains the habitat classes (then click "Next"). Only one field can be chosen per run.



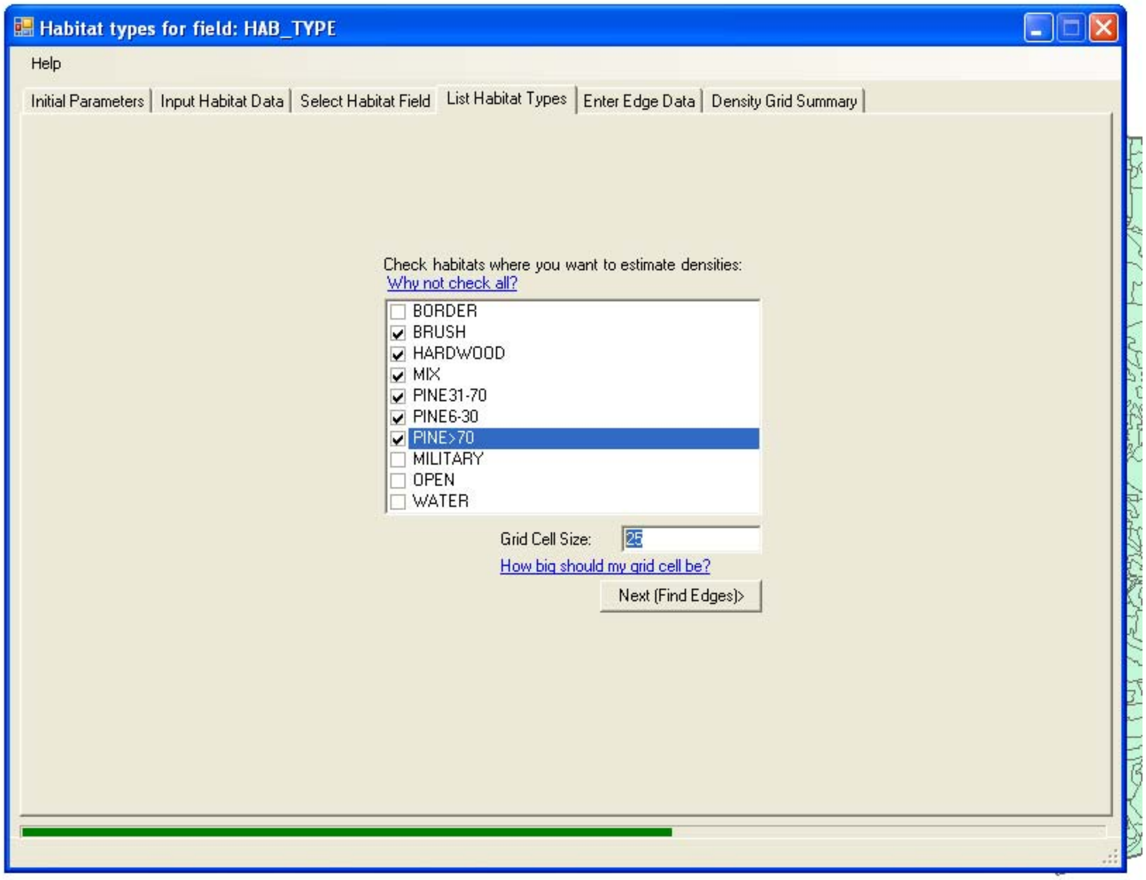
Note: if using a GRID, then the pixel values will automatically be used as the attribute type.

Step 5: List Habitat Types

Next, the EAM will show a list of all the unique values from the habitat field chosen in the previous screen (or the pixel values). This screen is also where the user can set the grid size (see below). Here, you must choose which specific habitat classes you wish to model. In the below example, only six of 10 habitat classes are chosen. This means that densities will be estimated only in those six habitat classes. However, the influence of all surrounding habitat on the edges of the modeled classes will be considered. For instance, in the above example, the user chose not to model responses within OPEN habitat. However, edge responses within any of the focal classes (i.e., HARDWOOD) adjacent to OPEN habitat will be modeled. This will be evident in the dialog box where edge response functions are entered (the next screen). In the above example, the user is required to enter responses to HARDWOOD|OPEN edges, but not OPEN|HARDWOOD edges.

CHOOSE AS FEW HABITAT TYPES AS POSSIBLE TO REDUCE THE NUMBER OF EDGE TYPES FOR WHICH PARAMETERS MUST BE ENTERED (AND TO REDUCE PROCESSING TIME)

During the next step, the EAM converts the habitat layer into a series of grid (raster) layers. The pixel or grid size will determine how much detail of the map will be captured. Smaller grids will capture more detail on the map, but require more processing time (so the model will take longer to run). A smaller grid size is also better able to



capture the shape of the edge response function. For instance, if Dmin is 10m and Dmax is 50m, but grid size is set to 100m, then gradations of habitat quality within the edge zone will not be captured. Also, if the average patch size is 10sq-m, but grid size is set to 100m, most patches will not be captured. On the other hand, if most patches are >1 ha, but grid size is set to 1m, that is likely too much detail and will require very high processing time with little additional gain.

The grid size is set by the user in the same dialog box illustrated above. Your map must be projected and in distance units (not decimal degrees). The units are the same as your map units (usually meters) and the default value is 5. Processing time is also based on the extent of your map. So, for maps that cover a large area, larger grid sizes will greatly reduce processing time. Choosing the optimum grid cell size that captures sufficient detail of your landscape and edge responses, but does not require inordinate amounts of processing time is another challenge that will require some thought on the part of the user.

After the focal habitat types and grid size has been chosen, the EAM will generate a series of habitat grids that will allow it to find all the unique edges associated with the focal habitat classes chosen. This process may take a long time, depending on the map extent and grid size that was chosen. A process bar lets the user know how much progress has been made.

Step 6: Enter Edge Data

When the EAM is finished finding all unique edges, it will move to the tab that shows a list of all the unique edge types and allows the user to enter parameters for as many focal species as they desire. Before entering parameters, the user should review the list of unique edge types. Depending on the way the user chose focal habitat classes, the list may be very lengthy. If so, the user may want to consider decreasing the number of unique edge types for which they must enter parameters. There are two ways of doing this: 1) reducing the number of habitat classes within the habitat field and/or 2) reducing the number of focal habitats to be modeled.

There are two reasons a user may decide to reduce the number of habitat classes. First, focal habitat classes may be too finely divided. For instance, a user might have a habitat layer that breaks forest into five categories: OLD-GROWTH PINE, YOUNG PINE, OLD-GROWTH HARDWOOD, YOUNG HARDWOOD, and MIXED stands. It may be prudent to reduce the number of forest classes. Possibilities to do this include pooling the original five categories into just three: PINE, HARDWOOD, MIXED or even just two: OLD-GROWTH PINE and OTHER FOREST. Second, non-focal habitat may result in too many edge classes. For instance, the user may be modeling responses only in FOREST, but have several other habitat classes that lead to edge types with similar responses. For instance, if there are four habitat classes representing habitats with open structure (such as AGRICULTURE, PASTURE, PRAIRIE, and UNVEGETATED), it may be prudent to reduce the number of non-focal habitats to a single class called OPEN. Ultimately, the solution will depend on the species being modeled as well as the available data.

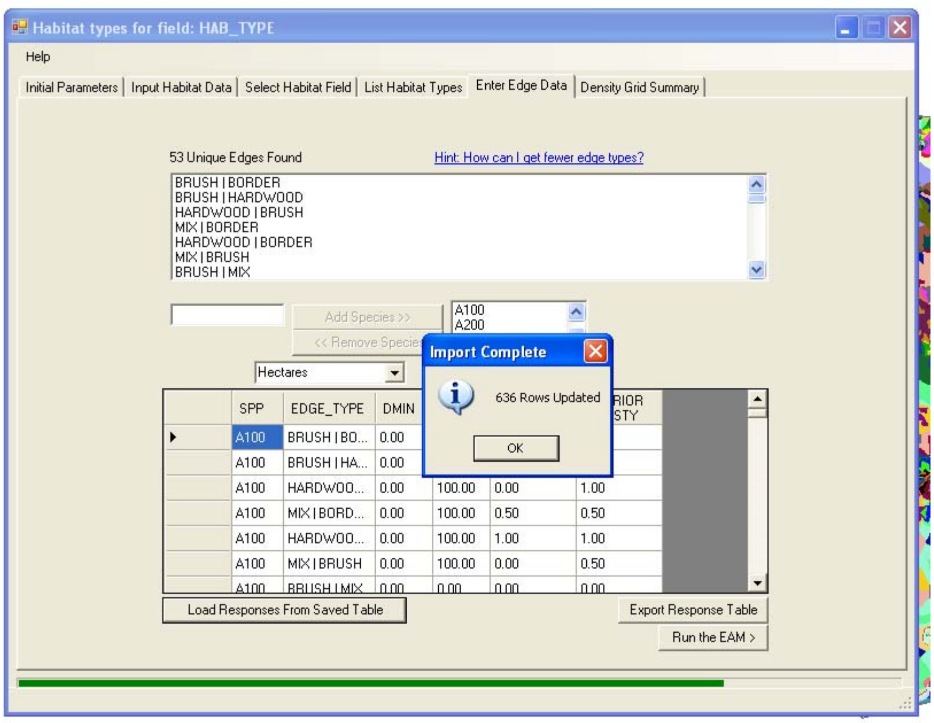
If the user decides that there are too many habitat classes, they must exit the EAM and modify the classes within the habitat layer's attribute table (or the grid values). If working with a polygon map, we suggest creating a new field in the attribute table rather than changing values in the current field. This preserves the original detail in habitat classes and allows flexibility for future modeling. See the ArcGIS user's manual if guidance is needed on creating new attribute fields and calculating values into those fields.

The second way to reduce the number of edge types is to reduce the number of focal habitats to be modeled. To do this, back up to the previous screen and uncheck whichever habitats you have decided not to model.

After completing any modifications necessary to reduce the number of edge types, the EAM next requires information on which species will be modeled. All edge response parameters are ideally kept in an external file that can be uploaded automatically into the EAM.

The first time you run the EAM for each map/species combination, you should create this file, which can be used each time the same system is modeled. To create the file, run the EAM up to the Enter Edge Data tab. Then add four-letter codes for each species you are interested in modeling. The EAM will add a record for each species/edge type combination. After all your species are added, then export the response table. It saves as a .csv file which launches into Excel, but you can load it into any program that reads text files. Enter and check all your edge data, then save the file. Alternatively, you can enter data directly into the EAM's dialog box, but we don't recommend this.

When you have the completed file (or if you are using reusing the same file from previous runs), you can load it into the EAM. Choose the button "Load Responses from Saved Table" and navigate to where you saved the file. Choose the file and it will load all the parameters into the dialog box. The EAM will show you that the rows are updated and you can also page through the table directly within the dialog box to check that the data loaded correctly.



After all edge response parameters are entered or loaded (and after checking for entry errors), click "Run the EAM".

<u>Step 7: Click "Run the EAM"</u>

This will now run the EAM

<u>Model mechanics and the generation of density grids</u>

After all the habitat information and edge response functions have been entered the EAM has started to run, the model goes through a series of steps where it carries out several calculations and generates several grids.

Prior to the last step, the EAM had already taken the polygon shape file and "rasterized" it, turning it into a grid or raster layer. If using grids, the EAM will recreate the grid files. This raster data map was loaded into ArcMAP with the title "habraster". Then, it parsed each habitat patch into sections based on what the closest edge is. This raster layer is called "Unique Edge Types" and shows where each unique edge type is in the landscape. Then, a grid with the distance to each of those edges was created.

After you load the Edge Response Functions and click "Run the EAM", the EAM then takes the edge response functions for each of the species and generates a density grid. The grid shows the predicted density in each grid cell. These predicted densities are based on the four edge response parameters entered for each species and the distance to and type of the closest edge.

In summary, when creating density grids, the EAM iterates through each pixel and determines 1) the closest edge type and 2) the distance to that edge type. Then, separately for each species, the EAM sets the predicted density value based on the following formulas:

Predicted density = Edge_Density if distance ≤ Dmin

Predicted density = Interior_Density if distance ≥ Dmax

If Dmin ≥ distance ≤ Dmax, then the predicted density is a linear function between the endpoints defined by Edge_Density (at Dmin) and Interior_Density (at Dmax).

Note that these cases use the four parameters entered for each edge response function and the EAM calls the edge response function separately for each pixel depending on the species and the closest edge type. As the EAM iterates through each pixel in the landscape, it creates a density grid that shows predicted densities for each species throughout the entire modeled landscape extent. These grids are loaded into ArcMAP and can be viewed or used as inputs into any program or analysis that reads raster-based layers or grids. The EAM also will summarize the values in these grids based on any values in the original habitat layer provided by the user.

DATA OUTPUT

<u>Density grids</u>

Density grids are the main product of the EAM. As the EAM completes its run, density grids for each species are generated and automatically loaded into ArcMAP. The values in these grids can be summarized or used in several ways. The final tab of the EAM dialog box allows basic summaries of the data to be generated and exported (see below). Alternatively, users who are comfortable with ArcGIS's rich analytical environment for grid data can perform any queries, summaries or modeling that they like. These grids could also be used as inputs for other analytical processes or programs such as Population

Viability Analyses (PVAs) or Decision Support Systems (DSS) that accept raster data. Finally, these grids are useful simply for visualizing the gradation of habitat quality and could be used for mapping and demonstrations.

For users that are interested in working directly with the resulting density grids, they can be saved in two ways. First, by choosing to save the run in Step 2 (Start Run), all grid products are saved (intermediate grids generated as part of the analytical process are discarded). The grids that are automatically saved with the run include the habraster, Unique Edge Types, EdgeDistance and all species' density grids. They are located in the folder the user specified when completing the first step along with a map document named the same as the run (i.e., Run1.mxd). If the run wasn't saved, but the user decides later to retain any of these grids, they can save them directly in ArcMAP by exporting them to a folder of their choosing (right click on the layer, and choose export). Otherwise, the output grids can be summarized using a dialog box that appears automatically after the EAM completes its run and these functions are described below.

Step 8: Density Grid Summary

If the user started with a polygon map, there is an option to summarize the density grids based on any field in the attribute table of the initial map. Generally, we have used a field giving a unique identifier to each patch, but any attribute field could be chosen. There are two types of summaries the EAM will produce, one for species metrics (Species Summary) and one for landscape metrics (Edge Summary).

Summary output can be saved into .csv files, which can then be imported into any program that reads text files. The format of these files can be used for analysis. We have developed a procedure to render these files into a format that we find particularly useful for analysis. That procedure has been automated within the statistical language R in a package called "REAM". The REAM package and instructions are available at the Edge Effects Resource Center.

Summarizing species responses

The EAM will summarize species' responses by integrating the pixels within specified regions of the landscape to come up with overall population predictions. The user specifies how they want the grids to be summarized by indicating which attribute field in their habitat map they want to use to stratify the summaries. For instance, the user may want to calculate population predictions for each unique patch containing their focal habitat types. If so, they will choose a field in the attribute table that contains a unique ID for each patch. After choosing the appropriate field, click "View Species Statistics".

When finished processing, the EAM will generate a Species Statistics table. This table summarizes the values in all species density grids and contains the following fields:

RunName: The name of the run you specified at the beginning of the EAM process
OID: An index field generated by Arc

SummaryField: Values are from whatever field was chosen to summarize the density grids. There should be a separate record for each unique value in the specified field in the original habitat attribute table. So, if the grids were summarized by PatchID, and there are 1000 unique patches on the landscape, there will be 1000 records in the Species Statistics Table for each species that was modeled.
ZONE_CODE: An ArcGIS field that is not informative
COUNT: The number of pixels contained within the regions bearing each unique value in the summary field
AREA: The total area of all pixels contained within the region bearing each unique value in the summary field. The value is the COUNT*grid area (specified by user)
MIN: The minimum value of the pixels in each summary region
MAX: The maximum value of the pixels in each summary region
RANGE: The range of values of the pixels in each summary region
MEAN: The mean value of the pixels in each summary region
STD: The standard deviation of the values of the pixels in each summary region
SUM: The sum of the values of the pixels in each summary region
TotalPop: The total number of individuals predicted to be in each summary region
SPP: The species density grid that was summarized

The Species Statistics table can be exported for analysis as a .csv (comma delimited) text file. This file can be read by any program that imports comma delimited files (such as Excel, Access, R or any other spreadsheet, statistics or database program).

Summarizing Edge Statistics

The EAM will also return summary statistics describing your landscape that may be helpful in determining underlying mechanisms for patterns observed in species distributions. The Edge Statistics table summarizes, for each unique value in the summary field, and for each unique edge type associated with the summary region, the cell count and the mean distance to edge for all the pixels in that summary region. A simple query on this table will also provide the number of unique edge types for each unique value in the summary field. Like the above summaries on species statistics, the user chooses which field from the habitat layer they want to use as a summary field. To generate the Edge Statistics table, click “View Edge Statistics”.

The EAM then returns a table with the following fields:

RunName: The name of the run you specified at the beginning of the EAM process
SummaryField: whatever field you chose to summarize your data. There should be a separate record for each unique edge type found within the summary region bearing each unique value in the specified field. So, if you summarized by PatchID, then the number of records will depend on how many unique edges are found patch by patch, and then totaled over the entire landscape.
EdgeType: Lists each unique edge type
CellCount: The number of pixels in the region associated with each unique edge type within each region with a unique value in the summary field.

MeanDistEdge: The mean value in the Edge Distance Grid for all pixels in the region associated with each unique edge type within each region with a unique value in the summary field.
AREA: The total area of all pixels contained within the region bearing each unique value in the summary field. The value is the COUNT*grid area (specified by user)

The Edge Statistics table can be exported for analysis as a .csv (comma delimited) text file. This file can be read by any program that imports comma delimited files (such as Excel, Access, R or any other spreadsheet, statistics or database program).

These two output tables will provide data summaries that can be used for analysis on how landscape structure impacts predicted organism distributions. The exact details of each analysis will differ depending on the question being asked.

When all summaries have been completed using the density grids, the user can exit out of the Density Grid Summary Screen. This effectively exits the user from the EAM. The resulting ArcMAP view containing all the generated density grids can be saved as an .mxd file. However, the run must have been saved in the initial steps of the EAM, otherwise the grids will be erased the next time the EAM is run.

TROUBLESHOOTING

Do not hesitate to contact lries@umd.edu with any problems. I'll try to get back to you as soon as possible and am happy to talk on the phone if that will be helpful. Below are some common problems.

I got an unhandled exception or notice of an error

In general, any time you get an error when running the EAM, we recommend exiting ArcMAP and starting over. This is because errors can sometimes alter "objects" that are part of the code and cause problems within a single session to persist. If the problem persists even after you restart ArcMAP, try rebooting your computer. If the problem continues, please contact lries@umd.edu.

My habitat classes don't appear in the Habitat Types screen

Back up and make sure that you checked the correct habitat field. If you did, open the attribute table of your habitat map and make sure the values are in the field that you think they are.

My parameters aren't loading into the edge parameter screen

Make sure that you saved your table as a .csv comma delimited file and that the headers and field values are the same as that in the dialog box. We have had problems when we have added our own records to the .csv table instead of adding them within the dialog box and exporting a table with all the records (but no edge response parameters) already there.

I'm having trouble backing up

Exit the program and begin the run again.

The density grids show patterns that do not make sense

Make sure that your map is "clean", in other words, there are no gaps or slivers between polygons and that there are no overlapping polygons. Also, double check your parameter entry and that you chose the correct habitat field to model. If your results still don't seem to match what they should based on your edge response parameters, contact lries@umd.edu

I can no longer choose items from lists within the EAM

Problems with the EAM interface (i.e., not being able to "choose" items from a list) may occur if your ArcMAP installation is corrupt or even some of the defaults have changed. Try going to add/delete programs, but instead of uninstalling ArcMAP, just run the repair utility. Make sure to uninstall the EAM first, then repair ArcMAP, then reinstall the EAM. If this doesn't solve the problem, contact lries@umd.edu.

GLOSSARY

Attribute table: Every polygon layer has an associated attribute table. This attribute table can contain multiple fields with information specific to each polygon within the layer. All information on habitat classes and attributes used to summarize density grids are found within this attribute table.

Context: A term that usually describes the habitat surrounding a patch. So patches may have a different context if they are surrounded by different habitat classes.

Edge: Edges can be defined in many ways, either from the point-of-view of the organism, the scientist, the manager, or the map-maker. However, for the purposes of the EAM, we define edges as the boundary between polygons of different habitat classes.

Dissolve: This is an ArcGIS function that takes a polygon layer, and "dissolves" adjacent polygons that contain the same value in the selected field of the attribute layer. We suggest dissolving polygon maps used as input in the EAM. This is not always necessary, but if summarizing the grid by patch, values such as mean distance to edge can give odd results.

Edge Response: There are many ways that organisms can respond to edges, including behavioral, with respect to vital rates, or through changes in distribution. For the purposes of the EAM, we model changes in density that can increase (positive edge effect), decrease (negative edge effect) or remain the same (no edge effect).

Edge Response Function: Generally, this refers to the shape of each organism's density response to the edge. In the EAM, this function is described by specifying an interior density, an edge density, the distance from the edge that edge effects extend (Dmax) and the width of the zone at the edge over which the edge density remains constant (Dmin).

Habitat: Although habitat specifically refers to the place where an organism lives, we use the term habitat loosely to mean various habitat types that usually refer to vegetation cover classes.

Habitat Class: For the purposes of the EAM, the list of different habitat types that the landscape of interest has been divided into.

Appendix C: Manual (Vignette) for the R-package “Edge-fx”

Note: This manual is bundled with the R-software and launches with the command “vignette” within R. In addition, a normal help guide was constructed in the format of R on-line guides, but is available on-line only

Using `edgefx` to compute the effects of habitat edges on a landscape

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January 12, 2010

Contents

1 Background

The edges of habitat patches affect species that live within the habitat. Often, edge effects are modeled as a simple function of distance to the nearest edge. Edge structure can be much more complex than that single-valued characterization, however. This package allows computation of edge effects due to all (or just nearby) edges in a landscape.

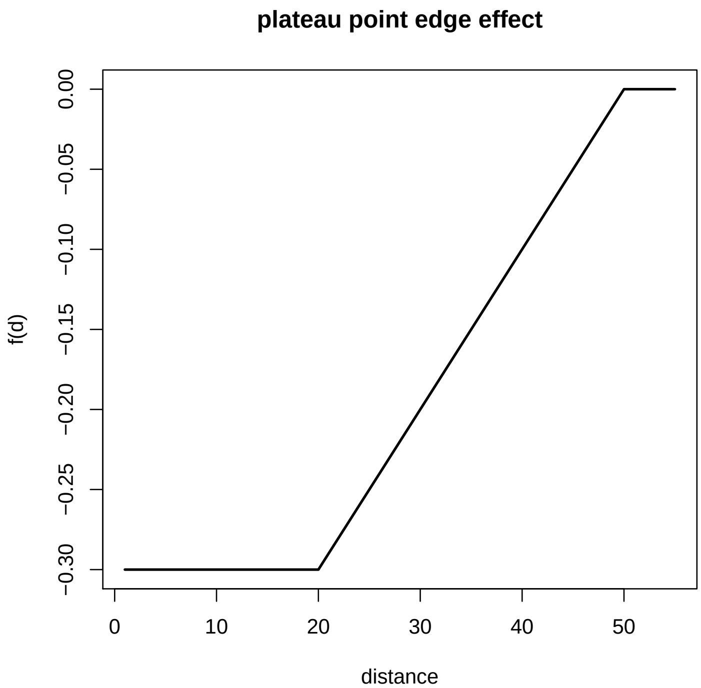
```
> library(edgefx)
```

Consider a response variable describing something about a species across space. For example, this could be the density of individuals, or the height of plants. Call it z. Say there is a baseline value far from any edges, k, and that edge effects cause deviations (either positive or negative) from this. Consider a particular point on the landscape where z is or could be measured; call it the "focal" point. Consider a second point that lies along a habitat edge and is a distance d from the focal point; call it the edge point. The effect of the edge point on the focal point can be modeled simply as a "plateau point edge effect,"

$$f(d) = \begin{cases} e_0 & d \le D_0 \\ e_0 \left(1 + \frac{D_0 - d}{D_{max} - D_0}\right) & D_0 < d \le D_{max} \\ 0 & d > D_{max} \end{cases} \tag{1}$$

where e_0 characterizes the maximum effect, D_0 is the distance out to which the maximum effect is felt, and D_{max} is the maximum distance at which any effect is felt. To see what $f(d)$ looks like, use `point.edge.effect()`:

```
> params <- list(e0 = -0.3, Dmax = 50, D0 = 20)
> d <- seq(params$Dmax * 1.1)
> plot(d, sapply(d, point.edge.effect, params), type = "l", lwd = 2,
+     xlab = "distance", ylab = "f(d)", main = "plateau point edge effect")
```



The simplest way of dealing with edges is to consider only the distance to the nearest edge, d_{min}, for each focal point [at position (x, y)], yielding

$$z(x, y) = k + f(d_{min}). \tag{2}$$

But this ignores the effects of other edge points, many of which may also be nearby. More complete would be to sum over all edge points within distance D_{max}, Γ, yielding

$$z(x, y) = k + \int_{\Gamma} f(s)\, ds. \tag{3}$$

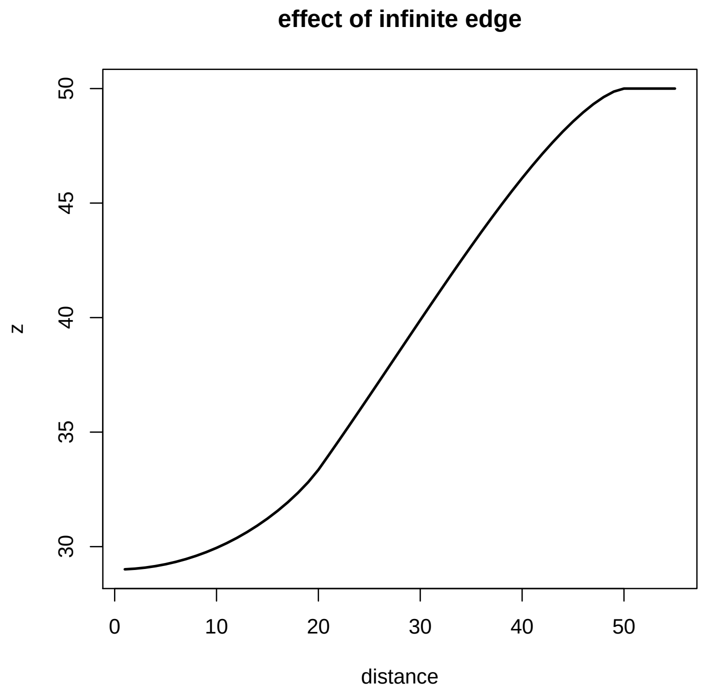
There are functions in `edgefx` to evaluate Eq.~3 for idealized infinite-extent edges, vector-based descriptions of finite habitat edges, and gridded habitat maps. Many of these procedures also allow estimation of the parameters in Eq.~1 from such data.

2 Infinite edges

2.1 Known parameter values

As an idealized case, consider an edge that is linear and infinite in extent. To evaluate Eq.~3 at a range of distances from the edge, using the plateau point edge effect shown above, use `infinite.edge.effect()`:

```
> params$k = 50
> plot(d, sapply(d, infinite.edge.effect, params), type = "l",
+     lwd = 2, xlab = "distance", ylab = "z", main = "effect of infinite edge")
```



2.2 Parameter estimation

Suppose you have edges in your landscape that approximate linear, infinite edges (or they don't really, but you want to make that assumption for comparison purposes). If you have observed values of your response variable, z, at a variety of distances from infinite edges, d, you can fit for the parameters in the point edge effect function (Eq.~1).

To see this in action, first generate some fake data:

```
> params <- list(e0 = -0.3, Dmax = 70, D0 = 20, k = 50)
> d <- seq(0, 100, 5)
> set.seed(3)
> z <- sapply(d, infinite.edge.effect, params) + rnorm(length(d))
```

Now use non-linear least squares to fit the infinite edge function, with and without the D_0 parameter:

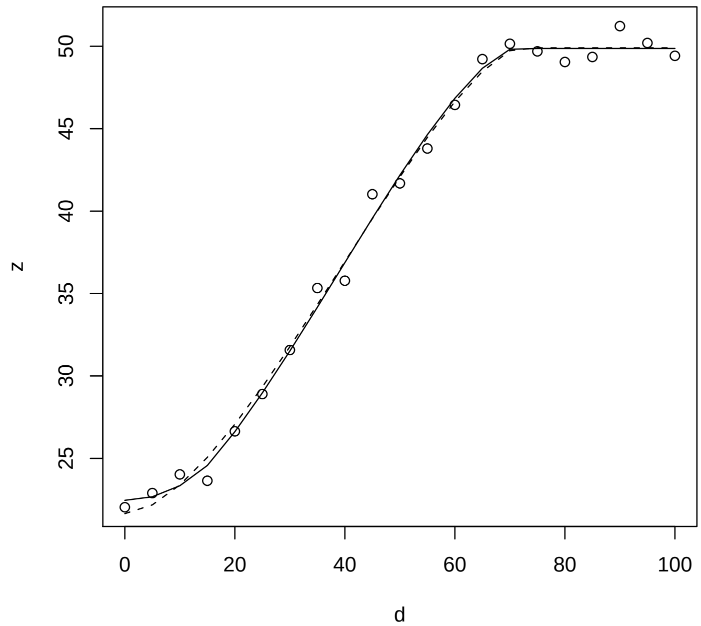
```
> nls.4par <- nls(z ~ sapply(d, infinite.edge.effect, e0, Dmax,
+     k, D0), start = list(e0 = -0.5, Dmax = 100, D0 = 40, k = 70),
+     algorithm = "port", lower = list(e0 = -Inf, Dmax = 0, k = -Inf,
+         D0 = 0))
> nls.3par <- nls(z ~ sapply(d, infinite.edge.effect, e0, Dmax,
+     k), start = list(e0 = -0.5, Dmax = 100, k = 70), algorithm = "port",
+     lower = list(e0 = -Inf, Dmax = 0, k = -Inf))
> summary(nls.4par)

Formula: z ~ sapply(d, infinite.edge.effect, e0, Dmax, k, D0)

Parameters:
     Estimate Std. Error t value Pr(>|t|)
```

```
e0   -0.31595    0.01976 -15.991 1.12e-11 ***
Dmax 70.66101    1.43764  49.151  < 2e-16 ***
D0   16.09796    4.58907   3.508   0.0027 **
k    49.86647    0.31088 160.405  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8008 on 17 degrees of freedom

Algorithm "port", convergence message: relative convergence (4)
```

```
> summary(nls.3par)

Formula: z ~ sapply(d, infinite.edge.effect, e0, Dmax, k)

Parameters:
      Estimate Std. Error t value Pr(>|t|)
e0   -0.394812   0.009778  -40.38   <2e-16 ***
Dmax 71.571193   1.334010   53.65   <2e-16 ***
k    49.905507   0.327551  152.36   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8362 on 18 degrees of freedom

Algorithm "port", convergence message: relative convergence (4)
```

To see the fits:

```
> plot(d, z)
> lines(d, predict(nls.4par))
> lines(d, predict(nls.3par), lty = 2)
```



To perform an AIC test of the two models:

```
> AIC(nls.3par) - AIC(nls.4par)
```

```
[1] 1.014882
```

The four-parameter model fits better (lower AIC score), but not substantially so (difference is less than 2). (But be a bit careful about potential bugginess in the `nls` methods of `AIC` and `logLik`.)

See Sec.~3.2.1 for notes on the `nls` options and convergence messages. It also shows a different method of fitting infinite edges using fake maps.

3 Vectorized landscapes

A real habitat won't consist solely of an infinite linear edge, but it can be approximated as a collection of finite edge line segments. Once you've turned the habitat edges in your landscape into line segments, you can use those edge descriptions along with observations of the response variable $z(x, y)$ to (1) estimate the parameters in the point edge effect function, e_0, k, D_0, and D_{max}, and (2) use parameter values (obtained through estimation or elsehow) to predict $z(x, y)$ anywhere in the landscape.

3.1 Input files

You should have a single input file for each focal point, containing the coordinates of the focal point and all the relevant edge segments. This package does not provide facilities for automatic identification of edges from general maps. Leslie will have notes on how best to get appropriate input files from GIS. But the per-focal-point files allow better customization of exactly which edge segments are "visible" to each focal point (e.g. don't include edges that are hidden behind other edges).

Here is an example of an input file:

```
# a comment
30, 50, ,    ,    focalhabitat
0,  0,  0,   100, edge1habitat
0,  0,  40,  20,  edge2habitat
40, 20, 100, 100, edge3habitat
```

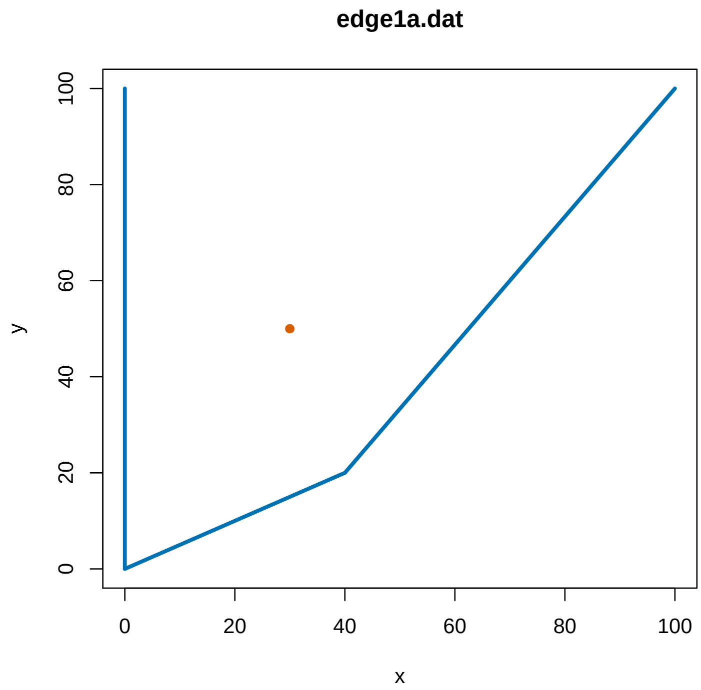
The origin of the coordinate system is arbitrary. The first non-comment line gives the x and y coordinates of the focal point; it needs two extra commas so R doesn't freak out about mis-matched numbers of columns. The rest of the lines are for the endpoints of each edge segment. The first edge extends from (0, 0) to (0, 100), the second from (0, 0) to (0, 40), etc. The last column is for notes about the habitat types, or whatever you want. Actually, you can have as many trailing columns as you want; their contents are ignored so far.

We've included a collection of simple edge input files for use here. You will have to identify where on your system they were installed. For me it is `/usr/local/lib/R/site-library/edgefx/doc/inputfiles/`, but for the compilation of this documentation, it is just `inputfiles/`. You should define `prefix` to be wherever you find them. Let's read the example files into a list.

```
> prefix <- "inputfiles/"
> filenames <- c("edge1a.dat", "edge1b.dat", "edge1c.dat", "edge1d.dat",
+     "edge1e.dat", "edge2a.dat", "edge2b.dat", "edge2c.dat", "edge2d.dat",
+     "edge2e.dat")
> edgefilenames <- paste(prefix, filenames, sep = "")
> edgelist <- lapply(edgefilenames, read.table, sep = ",")
> names(edgelist) <- filenames
```

Our `edgelist` now has ten elements, one for each file. Here's what the first one looks like:

```
> edgelist[[1]]

  V1 V2  V3  V4           V5
1 30 50  NA  NA     habitat1
2  0  0   0 100     habitat2
3  0  0  40  20     habitat2
4 40 20 100 100     habitat2

> draw.edges(edgelist[[1]])
> title(names(edgelist)[[1]])
```



The focal point is shown in orange, and its edges are shown in blue.

In our example, the first five input files all have the same edges but different focal points, and the same for the second five. You can combine analysis for whatever files you want, provided that you expect (or are willing to assume) that the same parameter values apply to all of them.

3.2 Parameter estimation

Now suppose that at each of the focal points, we have a measure of the response variable z. Let's read in those values.

```
> z.obs <- read.table(paste(prefix, "edgez.dat", sep = ""), header = T)
> z.obs
```

```
      map        z
1  edge1a 83.95431
2  edge1c 72.98649
3  edge1e 82.36007
4  edge2b 92.20720
5  edge2d 87.98545
6  edge1b 69.62626
7  edge1d 74.63733
8  edge2a 78.00661
9  edge2c 84.14898
10 edge2e 86.71185
```

Described next are two possible approaches for obtaining parameter estimates and their uncertainties from these data.

3.2.1 Non-linear least squares, via nls()

To estimate the parameter values, assuming normally-distributed errors, we can do a nonlinear least squares fit to the plateau point edge function integrated over all the edges for each focal point. So our dependent variable is `z.obs$z` and our independent variables come from the application of Eq.~3 to each matrix in `edgelist`. We need to provide a rough guess of the parameter values in order for `nls()` to get started.

```
> guess <- list(e0 = -0.1, Dmax = 80, k = 50, D0 = 5)
> edgefit <- edge.nls(edgelist, z.obs$z, guess)
```

You can pass additional arguments to `nls()` after `guess`, e.g., `trace=T`. To see how the fit did, use the result as you would any `nls` object, e.g.,

```
> summary(edgefit)

Formula: observed ~ by(edges[, 2:4], xvals, map.edge.effect, e0, Dmax,
    k, D0)[unique(xvals)]

Parameters:
     Estimate Std. Error t value Pr(>|t|)
e0   -0.27611    0.02547 -10.839 3.65e-05 ***
Dmax 42.47617    3.34888  12.684 1.47e-05 ***
k    97.20525    1.67003  58.206 1.73e-09 ***
D0   16.64404    3.40071   4.894  0.00273 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.692 on 6 degrees of freedom

Algorithm "port", convergence message: relative convergence (4)

> library(MASS)
> edgefit.profile <- profile(edgefit)

> confint(edgefit.profile)

         2.5%       97.5%
e0         NA  -0.2143116
Dmax       NA  49.8745073
k    93.46509 101.3459460
D0         NA          NA
```

Unfortunately, the `port` algorithm is required in order to constrain D_0 and D_{max} to be non-negative (this is applied within `edge.nls`), but `port` is "unfinished" (according to the `nls` help page). One consequence is that the `profile` and `confint` functions don't work reliably with `nls` results when `port` is used. But you'll have the standard errors from `summary`, even if `confint` gives `NA`s.

Support for a non-zero value of D_0 is pretty strong in this example, but often it isn't. To fit Malcolm's original point edge effect function rather than the plateau function, just omit D_0:

```
> guess <- list(e0 = -0.1, Dmax = 80, k = 50)
> edgefit <- edge.nls(edgelist, z.obs$z, guess)

> summary(edgefit)
```

```
Formula: observed ~ by(edges[, 2:4], xvals, map.edge.effect, e0, Dmax,
    k)[unique(xvals)]

Parameters:
     Estimate Std. Error t value Pr(>|t|)
e0    -0.3746     0.0415  -9.027 4.18e-05 ***
Dmax  44.0713     3.4590  12.741 4.25e-06 ***
k     96.5783     1.9805  48.764 3.99e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.942 on 7 degrees of freedom

Algorithm "port", convergence message: relative convergence (4)
```

```
> edgefit.profile <- profile(edgefit)
```

```
> confint(edgefit.profile)
```

```
           2.5%       97.5%
e0   -0.4700749  -0.2862819
Dmax 38.4377327  51.4741232
k    92.4350263 101.3855908
```

If you get a convergence message of anything other than `(0)` from `nls` (like the `(4)` we got here), it's best to try a variety of values for `guess`.

The function `edge.nls()` just provides a convenient wrapper to `nls()`. In case you want to tweak `nls`'s options yourself (or maybe try something else, like `nls2`), here are the extra steps to take. You can omit `D0` from `formula` and `guess` if you want. (Note: I don't know why `xvals` and `z` have to be defined separately, but R has a fit if they aren't.)

```
> edges <- relocate.edge.df(edgelist)
> xvals <- edges[, 1]
> z <- z.obs$z
> edge.formula <- formula(z ~ by(edges[, 2:4], xvals, map.edge.effect,
+     e0, Dmax, k, D0))
> guess <- list(e0 = -0.1, Dmax = 80, k = 50, D0 = 5)
> fit <- nls(edge.formula, start = guess, algorithm = "port", lower = list(e0 = -Inf,
+     Dmax = 0, k = -Inf, D0 = 0))
```

An alternative method for fitting to the infinite edge function (see Sec.~2.2) is to use the above procedure (or the one below, with `optim` or MCMC) but to replace the data frame of map information, `edges` above, with values that represent infinite edges, `inf.edges` here:

```
> n <- length(d)
> inf.edges <- data.frame(mapnames = paste("map", seq(n), sep = ""),
+     x0 = d, y1 = rep(-Inf, n), y2 = rep(Inf, n))
```

```
> head(inf.edges)
```

```
  mapnames x0   y1  y2
1     map1  0 -Inf Inf
2     map2  5 -Inf Inf
```

```
3      map3 10 -Inf Inf
4      map4 15 -Inf Inf
5      map5 20 -Inf Inf
6      map6 25 -Inf Inf
```

3.2.2 Generalized likelihood optimization and MCMC

An alternative to constrained optimization with `nls` is to deal with the (log)likelihood of the data directly, which the function `edge.lnL()` provides. For Gaussian errors, the log-likelihood is proportional to the sum-of-squared-differences, so using a general-purpose optimizer like `optim()` with `edge.lnL()` is in principle the same as using `nls()`, though you can specify different algorithms and ways to constrain parameter values. For Poisson errors, the likelihood function is computed slightly differently, but it can be used in the same way.

To use `optim()` directly (rather than through a wrapper as for `edge.nls()`) to obtain maximum likelihood parameter estimates, we have to abide by its rules. Specifically, the initial guess must be a vector (which can be obtained from a list by `unlist()`; if instead its elements are unnamed, they must be in the order e_0, D_{max}, k, and optionally D_0) and the value is minimized so the negative log-likelihood must be used (obtained from `edge.lnL()` with `neg=TRUE`). Additionally, it's a bit faster to pass `optim` the relocated edge dataframe (obtained via `relocate.edge.df()`) rather than the raw edge list.

Here is a sequence of examples:

```
> guess <- unlist(guess)
> edges <- relocate.edge.df(edgelist)
> optim(guess, edge.lnL, NULL, edges, z.obs$z, neg = T)

$par
         e0         Dmax            k           D0
 -0.3554509 1171.5757913  170.1661713   53.6657135

$value
[1] 367.7956

$counts
function gradient
     501       NA

$convergence
[1] 1

$message
NULL
```

Consult the `optim()` documentation to see that a convergence value of 1 indicates that the iteration limit has been reached. We can tell `optim()` to try for longer:

```
> optim(guess, edge.lnL, NULL, edges, z.obs$z, neg = T, control = list(maxit = 1000))

$par
         e0         Dmax            k           D0
 -0.3553188 1171.2919167  170.1306333   53.6656399

$value
[1] 367.7954
```

```
$counts
function gradient
     507       NA

$convergence
[1] 0

$message
NULL
```

The convergence value of 0 now indicates that the optimization was successful. The maximum-likelihood parameter estimates are given by `$par`, but these values are quite different from those from the `nls()` fit. We can find a higher likelihood (lower `$value`) by using different starting values:

```
> guess <- c(e0 = -0.3, Dmax = 50, k = 100, D0 = 5)
> optim(guess, edge.lnL, NULL, edges, z.obs$z, neg = T)

$par
        e0       Dmax          k         D0
-0.2761111 42.4766116 97.2051586 16.6432461

$value
[1] 17.17024

$counts
function gradient
     237       NA

$convergence
[1] 0

$message
NULL
```

Now the agreement with the `nls` result is perfect.

When an optimization method is not specified, the default is Nelder-Mead and the parameter constraints are taken care of by returning a likelihood value of `-Inf` when $D_{max} < 0$ or $D_0 < 0$. You could instead use the quasi-Newton method with box constraints on the parameter values (see the `optim()` documentation, and be sure that the order in `lower` matches that in `guess`):

```
> optim(guess, edge.lnL, NULL, method = "L-BFGS-B", lower = c(-Inf,
+     0, -Inf, 0), edges, z.obs$z, neg = T)

$par
        e0       Dmax          k         D0
-0.2761129 42.4761864 97.2052726 16.6440494

$value
[1] 17.17024

$counts
function gradient
```

```
      71       71

$convergence
[1] 0

$message
[1] "CONVERGENCE: REL_REDUCTION_OF_F <= FACTR*EPSMCH"
```

To fix $D_0 = 0$, simply omit it from the guess:

```
> guess <- c(e0 = -0.3, Dmax = 50, k = 100)
> optim(guess, edge.lnL, NULL, edges, z.obs$z, neg = T)

$par
        e0       Dmax          k
-0.3746541 44.0709961 96.5786155

$value
[1] 26.39620

$counts
function gradient
     140       NA

$convergence
[1] 0

$message
NULL
```

Everything above also applies to Poisson errors, which you can request with `family="poisson"`. Note that your observed values must be positive integers—this should be intrinsically true for real data, but it must be forced in this illustration:

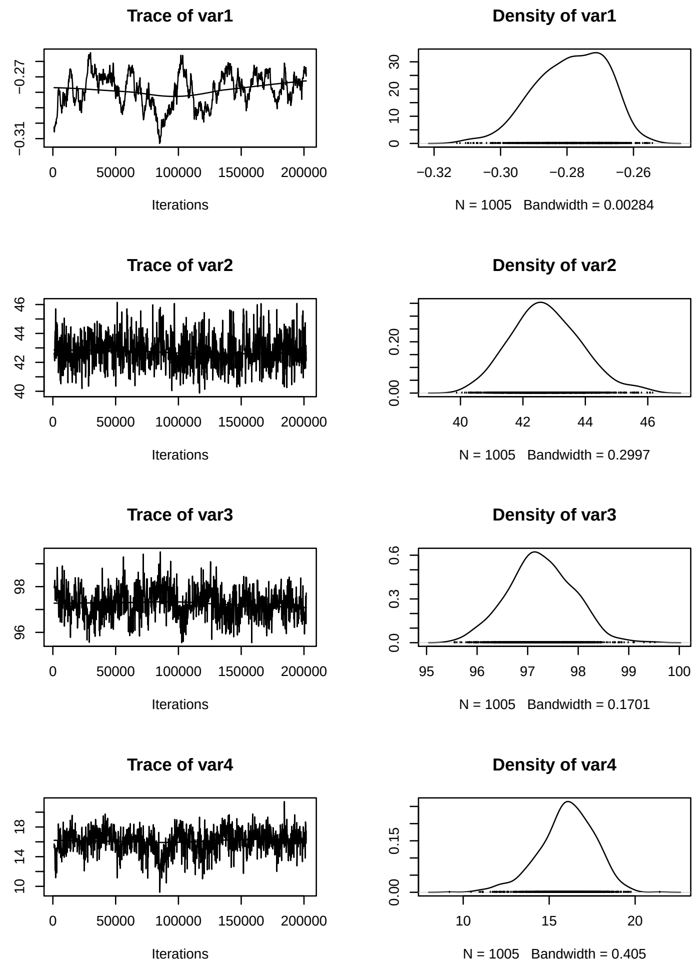
```
> guess <- c(e0 = -0.3, Dmax = 50, k = 100, D0 = 5)
> optim(guess, edge.lnL, NULL, edges, as.integer(z.obs$z), neg = T,
+     family = "poisson")

$par
        e0       Dmax          k         D0
-0.2801185 42.5425990 96.6676219 16.0719042

$value
[1] 31.28194

$counts
function gradient
     195       NA

$convergence
[1] 0

$message
NULL
```

Poisson errors often don't work well with `method="L-BFGS-B"` because negative predicted values must return a likelihood of `-Inf`, which this method apparantly can't handle.

Unlike `nls()`, `optim()` does not produce a structure for use by functions like `confint`. You could still map out the likelihood surface to get confidence intervals, but I couldn't find general-purpose R functions for that.

Alternatively, issues like uncertainty and correlation in the parameter estimates can be addressed by obtaining posterior distributions from Markov chain Monte Carlo. You will have to learn about proper use of MCMC elsewhere, including diagnosing convergence, but here is an example to start with. (It could also take `family="poisson"`, presumably.) The initial values are informed by the `optim()` results, to reduce the burn-in time. The tuning values were chosen by experimentation to yield an acceptance probability of about 20%. The thinning interval was chosen after looking at autocorrelation plots (`acf()` is useful for this). It takes awhile to run.

```
> library(MCMCpack)

> guess <- c(e0 = -0.3, Dmax = 50, k = 100, D0 = 20)
> edgemcmc = MCMCmetrop1R(edge.lnL, guess, burnin = 1000, mcmc = 201000,
+     thin = 200, tune = c(0.1, 1, 1, 1), optim.method = "Nelder-Mead",
+     edgecoord = edges, observed = z.obs$z)

@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@
The Metropolis acceptance rate was 0.26666
@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@

> plot(edgemcmc)
```



> summary(edgemcmc)

```
Iterations = 1001:201801
Thinning interval = 200
Number of chains = 1
Sample size per chain = 1005

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

        Mean      SD  Naive SE Time-series SE
[1,] -0.2788 0.01068 0.0003368       0.001690
[2,] 42.7434 1.12665 0.0355390       0.042792
[3,] 97.2555 0.63961 0.0201759       0.042251
[4,] 16.0457 1.60456 0.0506142       0.114726

2. Quantiles for each variable:

        2.5%     25%     50%     75%   97.5%
var1 -0.3015 -0.2861 -0.2781 -0.2704 -0.2618
```

```
var2 40.6454 41.9654 42.6749 43.4879 45.2359
var3 95.9890 96.8341 97.2294 97.6966 98.4394
var4 12.3598 15.1368 16.1176 17.1772 18.8182
```

4 Gridded landscapes

As mentioned above, `edgefx` does not have sophisticated edge-detection functions. For a gridded landscape, the most it will do is identify as edges the cells of non-habitat ("matrix," but I'll avoid that term since it is also an R data structure) that have, among their four neighboring cells, at least one habitat cell. The response value z at each cell in the landscape can then be predicted as the sum of effects from all identified edge cells.

The distance between two cells is defined to be 1 for adjacent cells, and can be found for any pair of cell coordinates like so:

```
> distance(c(2, 3), c(4, 7))
```

```
[1] 4.472136
```

If you have existing parameter estimates and want to apply them here, you may have to do a unit conversion. The exact conversion will depend on what you have, but here is an example. Say your observations, z, are the number of individuals per grid cell of size length a. And say that when you estimated the edge function parameters (e_0, D_{max}, k, and maybe D_0), you gave distances in meters rather than number of grid cells. Since D_{max} and D_0 have units of length, the adjusted values you should use with the unit grid cells here are $D'_{max} = D_{max}/a$ and $D'_0 = D_0/a$. Since k already has units of per grid cell, $k' = k$. Since e_0 has units of individuals per length, $e'_0 = e_0 \times a$.

4.1 Input files

Here is an example of an input file for a gridded landscape. Note that `0` signifies non-habitat, any other positive number signifies habitat, and spaces signify borders between cells (this allows habitat codes of more than one digit).

```
0 0 0 0 0 0 0 0 0 0 0 2 2 2 2
1 1 1 1 1 0 0 0 0 0 0 0 2 2 2
1 1 1 1 0 0 0 0 0 0 0 2 2 2 2
1 1 1 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 1 1 1 0 0 0 0 0 0 0 1 1
```

Let's read that particular habitat file into a matrix:

```
> map <- read.table(paste(prefix, "smallgrid.dat", sep = ""))
> map <- data.matrix(map)
```

I found it easier to visualize the landscape with slightly different formatting. The function `write.grid()` produces a file, whose contents are printed below. You can find the example files near the `prefix` you defined above (replace `inputfiles` with `outputfiles`).

```
> write.grid(map, "outputfiles/smallgrid.map")
```

```
           ....
.....       ...
....       ....
...
...
......       ..
```

The next step is to identify the cells that are edges. This can be slightly slow for a large landscape. You may also want to write those results to a file for visualization/checking.

```
> edges <- find.edges(map)
> write.edges(map, edges, "outputfiles/smallgrid.edge")
```

creates a file that contains:

```
xxxxx    x
     x    x
    x    x
   x      xxxx
   xxx      xx
      x    x
```

4.2 Response prediction

To compute the response value for each cell, we first need to provide parameter values for the plateau point edge effect function.

```
> params <- list(e0 = -0.3, k = 5, D0 = 0, Dmax = 10)
```

Then we can use `grid.effects()` to treat each habitat cell in turn as the focal cell and compute its response value, z. This step can be slow for a large grid and large values of D_{max}.

```
> z <- grid.effects(map, edges, params)
```

The result is a vector with one item per cell, ordered by column (read down column 1, then read down column 2, etc.). These values are the predicted responses for habitat cells, and `NA` for non-habitat cells. If you didn't want to include some cells identified as edges, you could just remove them from `edges` before calling `grid.effects()`.

To print the results in either tabular or graphic form, you have to take some care to get the orientation of the landscape right. For example, here is how to view `z` in the same orientation as the `map`:

```
> matrix(z, ncol = ncol(map))
```

```
         [,1]     [,2]     [,3]     [,4]     [,5]     [,6] [,7] [,8] [,9] [,10]
[1,]       NA       NA       NA       NA       NA       NA   NA   NA   NA    NA
[2,] 2.757224 2.391091 2.064658 1.761261 1.509462       NA   NA   NA   NA    NA
[3,] 2.778329 2.406429 2.046681 1.702641       NA       NA   NA   NA   NA    NA
[4,] 2.867153 2.501380 2.121457       NA       NA       NA   NA   NA   NA    NA
[5,] 3.019753 2.676498 2.302272       NA       NA       NA   NA   NA   NA    NA
[6,] 3.221152 2.925479 2.582877 2.249200 1.953873 1.756154   NA   NA   NA    NA
        [,11]    [,12]    [,13]    [,14]
[1,] 2.005296 2.304855 2.648967 2.989033
[2,]       NA 2.016763 2.371094 2.747569
[3,] 1.555564 1.826897 2.168306 2.565966
[4,]       NA       NA       NA       NA
[5,]       NA       NA       NA       NA
[6,]       NA       NA 2.388755 2.727175
```

And here is how to write a file for `z` that has the same cell layout as the input file.

```
> write.table(matrix(z, nrow = nrow(map)), file = "outputfiles/smallgrid.z",
+     na = "NA", quote = F, sep = " ", row.names = F, col.names = F)
```

If your input map had a variety of habitat codes and you want to extract the values of `z` that go with each, you can do it like this.

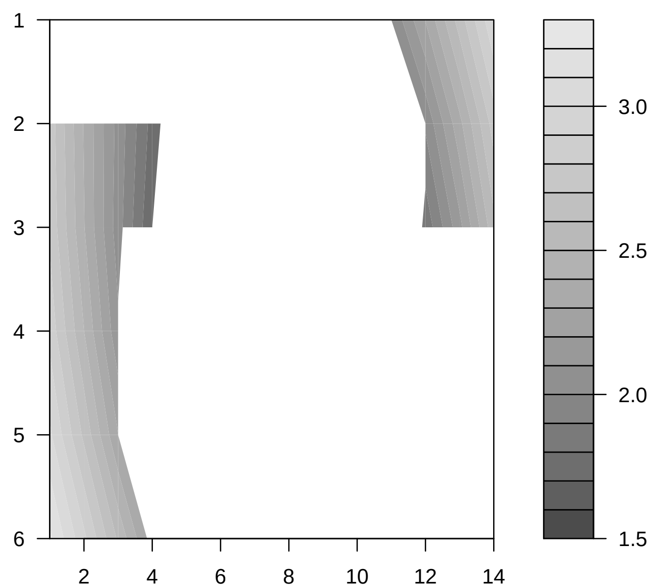
```
> m <- as.vector(as.matrix(map))
> hcodes <- list(one = 1, two = 2)
> sapply(hcodes, f <- function(x) z[m == x])

$one
 [1] 2.757224 2.778329 2.867153 3.019753 3.221152 2.391091 2.406429 2.501380
 [9] 2.676498 2.925479 2.064658 2.046681 2.121457 2.302272 2.582877 1.761261
[17] 1.702641 2.249200 1.509462 1.953873 1.756154 2.388755 2.727175

$two
 [1] 2.005296 1.555564 2.304855 2.016763 1.826897 2.648967 2.371094 2.168306
 [9] 2.989033 2.747569 2.565966
```

To plot the results, turn `z` into a matrix in what seems like the wrong orientation:

```
> z <- matrix(z, byrow = T, ncol = nrow(map))
```

Here's a basic plot of the result.

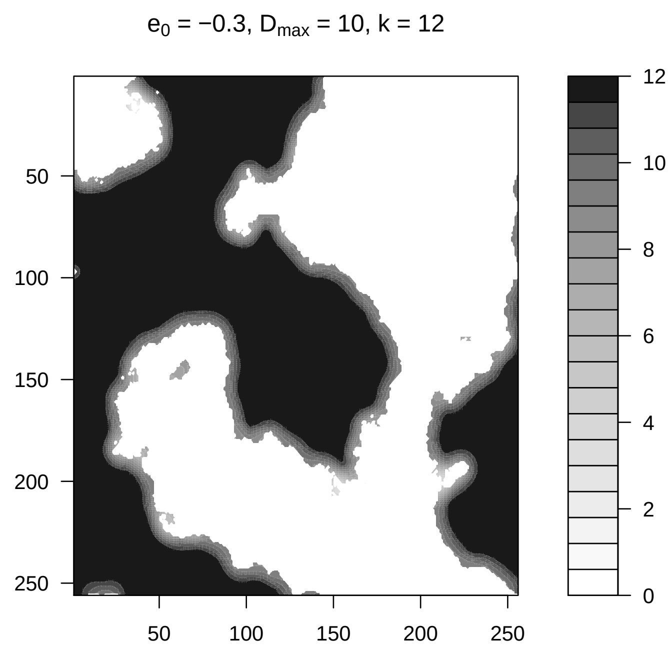
```
> filled.contour(seq(ncol(map)), seq(nrow(map)), z, ylim = c(nrow(map),
+     1), color.palette = gray.colors)
```



(You might instead want to use `contourplot` from the `lattice` package, which uses a clearer formula notation.)

That's not such an exciting landscape. Here's a more elaborate one (the interior areas are black, but it seems that gets lost in the pdf conversion):

```
> map <- read.table(paste(prefix, "biggrid.dat", sep = ""))
> map <- data.matrix(map)
> edges <- find.edges(map)
> params <- list(e0 = -0.3, k = 12, D0 = 0, Dmax = 10)
> z <- grid.effects(map, edges, params)
> z <- matrix(z, byrow = T, ncol = nrow(map))
> label <- substitute(expression(paste(e[0], " = ", e0, ", ", D[max],
+     " = ", Dmax, ", k = ", kval)), list(e0 = params$e0, Dmax = params$Dmax,
+     kval = params$k))
> filled.contour(seq(ncol(map)), seq(nrow(map)), z, ylim = c(nrow(map),
+     1), col = gray.colors(20, 1, 0.1), levels = seq(0, params$k,
+     len = 21), main = eval(label))
```



If the computations are slow and you only want responses predicted for a portion of your landscape, you can create a dataframe of focal cell coordinates and just use those. For example, to predict on just a strip in the upper left corner:

```
> focals <- data.frame(row = rep(seq(5), 2), col = c(rep(1, 5),
+     rep(2, 5)))
> focals

  row col
1   1   1
2   2   1
3   3   1
4   4   1
5   5   1
6   1   2
7   2   2
```

```
8    3   2
9    4   2
10   5   2
```

```
> z <- apply(focals, 1, grid.edge.effect, edges, map, params)
```

Appendix D: Instructions for the R-package “REAM”

Note: This package performs only two functions (compiling and restructuring EAM output and producing preliminary graphs for visualization) so we did not develop an in-depth manual

Instructions for the REAM package

Install REAM.zip from local hard drive to R 2.10 or greater

The FIRST time you do this, you will have to go to the CRAN mirror to install reshape and plyr

Launch REAM >library(REAM)

Before you start – you must have your files set up following this very strict format:

In a root directory (can be called anything) on your local drive (we have not been able to have this work over a network) you must have two folders and two files AND NOTHING ELSE!

All names must be EXACTLY as listed (except where noted)

Two folders:

1) Edge Output

This folder contains all the output .csv files from running the EAM edge statistics. Each file should match a run name and be named: “RunName”_edge.csv – with the run name filled in.

2) Species Output

This folder contains all the output .csv files from running the EAM species statistics. Each file should match a run name and be named: “RunName”_edge.csv – with the run name filled in.

Note: Make sure the third field in all these output tables is called SummaryField (sometimes it gets named after the field used to summarize)

Two Files:

1) Edge response parameters (This file can be named anything): .csv file with all your edge response parameters (this should be the same file you used to load the edge response statistics while running the EAM to output the files in the folders listed above.

2) Scenario table: .csv file with three columns “RunName” “MapType”, “Action”.

After loading the REAM package, there are only two commands:

EAM_database_processing(Root directory where the above four objects are located, Name of edge response file)

For instance:

EAM_database_processing("C:\\Documents and Settings\\Administrator\\Desktop\\EAM Output New Headers","Edge Response

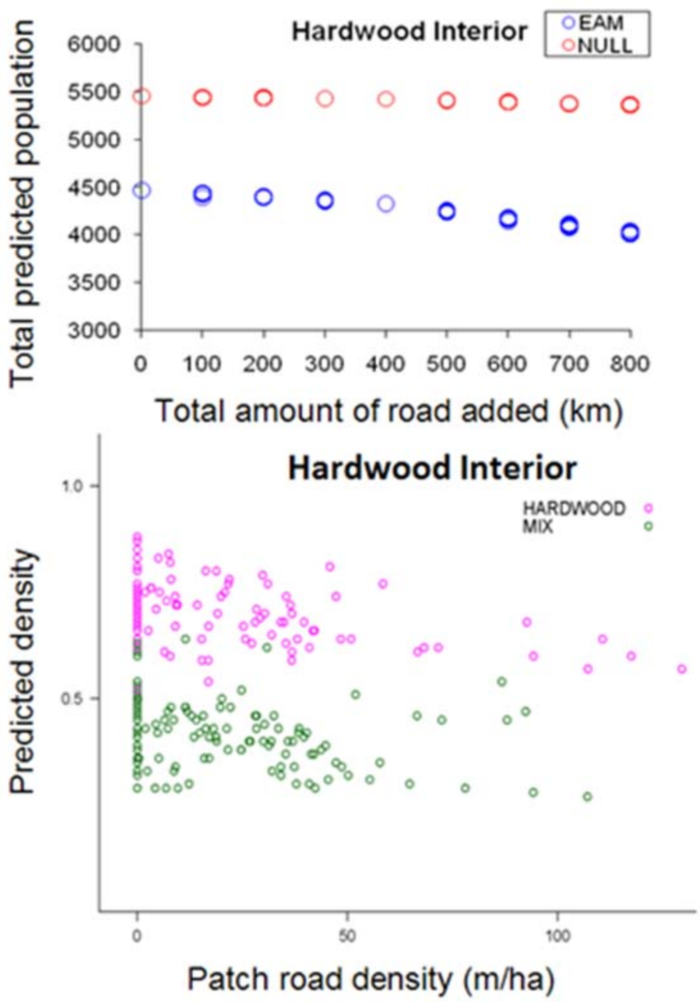
```
Parameters.csv")
```

The first parameter is the path to the working directory, the second is the name of the Edge Response Parameters file.

The second command is to generate two figures that show patterns on the landscape and patch scales (see below). The function is launched with the command:

```
EAM_graphing(base_directory)
```

Where the base_directory is the same directory where all files are contained (see above).



Graphs output automatically by the custom R-package REAM showing landscape scale (a) and patch-level (b) results.